# Negotiation in a modular manufacturing process

*Master Thesis v 0.4*

**Diederik van Krieken**
Artificial Intelligence
Univeristy of Groningen, the Netherlands
d.r.j.van.krieken@student.rug.nl
S2009730

Internal supervisor:
Rineke Verbrugge (Artificial Intelligence, RUG)

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# Contents

# Chapter 1

# Introduction

This thesis is written as part of the Master Artificial Intelligence at the University of Groningen on behalf of the Multi-Agent Systems (MAS) group. The MAS group is part of the Artificial Intelligence and Cognitive Engineering (ALICE) research institute. This group is led by L.C. (Rineke) Verbrugge.

## 1.1 Introduction in Production, AI and the use case environment

Currently there is a lot of research being conducted in Artificial Intelligence(AI) and how to apply this in business. One field of interest, which is researched in this thesis, is the combination of Multi-Agents Systems in Production.

### 1.1.1 Production and Manufacturing

Production is the process of converting inputs into outputs. It is one of the economic pillars on which the economic markets are driven. By creating extra value from basic commodities, a (perceived) contribution to the well-being of individuals is conceivable. Manufacturing is a specific subsidiary of production, and is the process of converting (raw) material into semi and/or finished end products by using various processes, machines and energy. Thus, every type of manufacturing can be production, but not every type of production is manufacturing. The production and manufacturing industry is and will be one of the wealth generators of the world economy (Monostori et al., 2006), and is characterised by the production of commodities that have value and contribute to the well-being of individuals.

In the industrial production world, a 4th revolution is going on, which enables the world to think about new production processes. The First Industrial Revolution was the use of steam power to mechanize production. In the second revolution, the use of electric power allowed for assembly lines, resulting in mass production. The third revolution used electronics and information technology to automate production. Now a fourth industrial revolution, also called Industry 4.0*, is building on the third, and is called the digital revolution. It is characterized by a fusion of technologies that is blurring the lines between the physical and digital (Leitao et al., 2016).

Throughout this thesis, the terms production and manufacturing will be used interchangeably. This does not mean that the terms are interchangeable in general, since in the industry there is a difference. However, for this research, due to the similarity in the sense of the processes, no separation is needed. This is supported by the exchangeability of the terms in the literature.

### 1.1.2 Artificial Intelligence

The research will be based on an intelligent Multi-Agent System (MAS) which would consist of sensors, and processors which act and react on their environment in both a physical as in an IT way. For the intelligent agents it would be possible, by understanding the system, and by negotiating, to come up with a (near-) optimal production planning, taking in consideration possible maintenance and downtime, based on real-time data acquisition, analysis, negotiations and decentralized autonomous decision making. Such intelligence is an example of a typical MAS where artificial intelligence may include methodical, functional, and procedural approaches, algorithmic search and/or reinforcement learning.

### 1.1.3 Ecosystem of the case study

In this thesis a new model will be constructed based on negotiation in an intelligent Multi-Agent System. An application of this new model is tested and modelled based on a plant that creates de-mineralized water. By removing all the ions from common water, de-mineralized water is obtained. This water is used for many different processes, and has many applications. In this plant specifically it is used for the steam turbines, which generate electricity. By burning the by-product, heat is generated, which creates steam to power the turbines.

Minerals are removed from water by multiple production steps. Most common, and as is implemented in the plant described, is to first remove the positively charged minerals in so called anions. After this the negative charged ions are removed within a cation filter. To ensure that all ions are removed, a final

*This revolution has multiple terms in multiple countries. For example, Industrie 4.0 in Germany, Smart Manufacturing or Smart Industry in the Netherlands, or the Industrial Internet Consortium in the U.S.A. In this thesis the term Industry 4.0 will be used.

combined “mixbed” is used. Here a combination of an anion and cation filter removes the residues.

These filters have to be cleaned every few hours to ensure that proper demineralization occurs. By optimizing the production planning, real-time predicting where cleaning is necessary is possible, resulting in minimal waste.

## 1.2 Thesis outline

In Chapter 2 an overview of the problem is given. Chapter 3 will explain the literature regarding manufacturing and negotiation. This also includes an overview of the methods. From this a framework is concluded with, which is used to design and implement our model, the foundation of Chapter 3. In Chapter 4 the model is tested and evaluated by simulation. From this we can conclude and generalize for further use as described in Chapter 5.

1. Introduction
2. Problem definition
3. Literature Study & Theoretical framework
4. Design & Computational Implementation
5. Simulation comparison incl evaluations
6. Discussion & Conclusions

# Chapter 2

# Problem Definition & Research Goal

An overview of the problem will be given, and based on the findings, the research goal will be discussed. Important is to define the relevance and approach to the entire research.

## 2.1 Problem Analysis

Due to the 4th industrial revolution, new production and manufacturing methods are required which need new digital solutions to optimize the planning. One solution is centralized analysis, combining all the data in a central database and analysing this to optimize decision making. Another solution, which is decentralisation, analyses the data on several different points, which independently create decisions. One of the decisions for the implementation of such a system requires many considerations. Currently it is not fully clear what requirements depend on the implementation (Leitao et al., 2016). Also, the practically of different negotiation frameworks is unknown (Fatima et al., 2014b). For example, a necessity might be the requirement that the process is subject to change. If expanded or changed, many modifications in a centralized system are required since the central database has to relearn the patterns, and new databases might have to be set up. This might, however, not be the case with decentralized solutions.

A second problem is that the amount of data nowadays is enormous and as a result large quantities of data are pouring on-line, waiting to be processed in the centralized database. Furthermore, much of the data is not processed from the sensor towards the centralized database, resulting in incomplete analysis. There is an overall consensus that the future of industry 4.0 lies with pre-aggregated data (Slaughter et al., 2015) which is obtained by having the sensors think and reason about the measurements before sending the processed information to a central database.

Thirdly, scheduling production problems are Non-deterministic Polynomial (NP)-hard problems that are very complex to solve using (mixed) integer programming and take a very long time to find an optimal solution. There is a consensus that Multi-Agent scheduling retrieves a (suboptimal)-solution in reasonable time (Konolige and Nilsson, 1980). Since scheduling is NP-hard, this solution does not have to be the optimal solution but a "good enough" result.

The new developments in the industries, like the use of Internet of Things (IoT) require manufacturers to rethink their production. An IoT is a network where many sensors are connected using different web protocols or protocols specifically designed for IoT. These sensors retrieve their data and share the information via this network and usually communicate with a centralized database, where the data of the sensors is analysed. After analysing, production can be planned resulting in lower down time of the asset and more efficient production. When these systems are embedded, they are also known as Cyber-Physical Systems (CPS).

## 2.2 Area of Application

Currently an industry leader in the production of steal is looking to optimize their de-mineralized water production. Currently their production process is done by hand, and no digital optimization method is currently in place. Furthermore, a substantial amount of some very costly materials is "discarded" due to legislative requirements. By using these materials instead of dumping them, cost can be reduced.

As the main scope of this research project is aimed at negotiation, the planning under consideration will undergo some idealization meaning, that it will not be too constrained. This leaves for example, specific training levels of the mechanics out of scope. Furthermore, the possible difficult operations are excluded. If time allows it, more constraints can be included.

## 2.3 Relevance

The research will be relevant for two different stakeholders, the academic and business world. Business has always been dependent on the academic world, and by connecting these, new valuable insights can be combined.

### 2.3.1 Scientific relevance

Currently there are not a lot of papers discussing the use of negotiation in a multi-agent solution for manufacturing. There comprehensive overviews, but the negotiation aspect is a commonly lacking subject (Leitão, 2009). In chapter 3 a comprehensive overview will be given. By researching and, importantly, and computationally implementing the use of negotiation in distributed production planning, the theory can be connected to real life cases. This is based on the classic artificial intelligence problem, which is the combination of information and objectives from different sources and will be solved with a Multi-Agent System.

This research is about the application of multi-agent system technology, negotiation, game theory and decision making. Knowledge from AI about negotiation will be used to obtain new insights in possible decentralized production solutions.

For me personally this research project would be a perfect way to find out how ideas and solutions in the AI literature can be used to describe and improve large-scale and real-world solutions.

### 2.3.2 Business relevance

The business has difficulty in the transformation to the new industrial pillars. Enormous amounts of data, and new requirements ask for "on top of the line" production systems. By computationally implementing one of the processes and optimizing these processes, these insight can be applied for further use.

## 2.4 Research Goal

The main goal is to create a production planner using a Multi-Agent System with negotiation. This is divided into the following sub-goals:

1. Provide a theoretical framework for negotiation in a Multi-Agent System in the context of manufacturing/production planning incl predictive maintenance and/or process control.
2. Create a demonstrator of this framework to show that a Multi-Agent System can be used for manufacturing/production planning incl predictive maintenance and/or process control.
3. Provide new maintenance management insights;
4. Determine what application contexts profit of the creation of such a new Multi-Agent System.

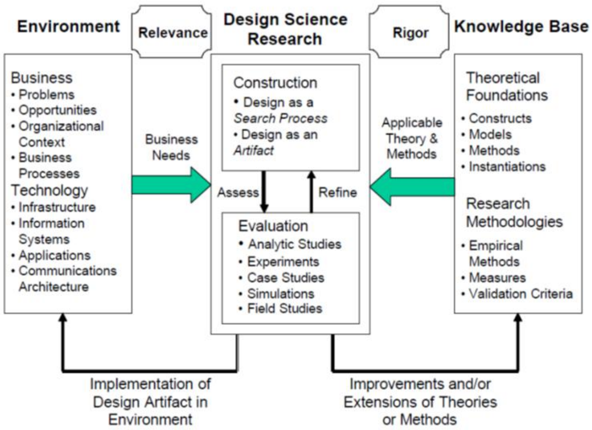


Figure 2.1: The Information System Research Framework as designed by Hevner and Chatterjee (2010)

## 2.5 Research Approach

Since this is an academic research project, a new MAS framework will be investigated and constructed. The working and exact results will be analysed by the use of a demonstrator. This falls under the computational implementation and modelling of a new MAS framework. This excludes the verification (use users to control your theory) & validation of the system.

The research framework used will be based on Hevner and Chatterjee (2010) and can be seen in Figure 2.1. The aim of the relevance cycle is to connect the real-world environment of the research project with the design science activities. Through this relevance cycle, opportunities for the improvement of practices can be identified.

The rigor cycle is used to assemble a knowledge base that consists of the relevant theoretical foundations and research methodologies. Prior research provides a starting point and benchmark for new artefacts. This knowledge base is necessary to establish theoretical appropriateness and relevance, achieving rigor.

In this research, a case-study is included to ensure the relevance of the new MAS framework. By comparing the model with a real-world situation, the new MAS framework can be assessed and maybe refined.

## 2.6 Research Process

Firstly a literature research was concluded to assess the current negotiation methods in agent manufacturing systems. Afterwards a mapping of the processes, clarification of the objectives and determination of the requirements related to the use-case was performed. It was important to define the boundaries of the context system and the evaluation method before the system was built.

Based on this framework, a mathematical model, to assess how the negotiation will concur in the multi-agent system, will be created. A simulator will be created to evaluate this method. After the creation of the model and simulator, the relevance will be assessed by it's performance.

The operational requirements should be clear then, and the theory can match the business expectations. From this, future prospects can be concluded.

### 2.6.1 Evaluation Method

To test the final theoretical framework, a virtual simulation is to be created. The sensors/agents can be shown, including what they know and for example their gauge values. In such a simulation, the negotiation can be visualized, and proof for the (near-)optimal outcome can be shown. By having a few variable sliders on the display, a user might change some variables which would show an increase/decrease in negotiation and optimal solution time.

Depending on the eventual data source, two evaluation methods are possible. If a "real" data source is available, the Key Performance Indicator (KPI) of the business will be checked. By minimizing e.g. the consumed base and acid during the production process, an improvement of the new system can be concluded.

If a "real" data source cannot be found, a second model is to be implemented. Using this other, probably heuristic or Linear solution, a comparison between the new method and the other method can be conducted and evaluated in aspects of speed, quality solution, and dynamicity.

## 2.7 Research Questions

From the research goals and process, the following research questions are concluded:

1. How can energy and manufacturing companies use the AI concept of intelligent multi-agent systems (MAS) for the optimization of production planning incl predictive maintenance and/or process control optimization?
    (a) What is the optimal MAS framework for the optimization of production planning?
        i. Theoretical: Which negotiation techniques, communication protocols, knowledge models and hierarchy/coalition to optimize decision making/scheduling.

ii. Simulation: Compare the new framework to an old use-case using simulation results.

(b) What is the roadmap for other industries within the industry 4.0?

i. Decentralized systems vs Centralized systems

ii. Negotiation in manufacturing

# Chapter 3

# Literature Study & Theoretical framework

The manufacturing industry is and will be one of the wealth generators of the world economy. A shift towards a modular production process, the 4th industrial revolution (also called Industry 4.0 transition), results in a demand for products with high quality at lower cost while being highly customized. This results in new way of controlling the production. High-performing computing, the internet, universal access and connectivity, and enterprise integration all contribute. Overall the consensus is that only the companies that fully leverage the information, its availability, the ability to exchange it seamlessly, and process it quickly, are the companies that can meet the high demand of the consumers (Monostori et al., 2006).

The so-called agent-based computation is a solution for many of the problems that arise from this new trend. By having autonomous agents, who can address changes adaptively and are distributed in nature, intelligent solutions are available (Monostori et al., 2006).

In this literature review, an overview of the manufacturing processes and current agent technologies/solutions are given. Using such a decentralized agent solution is only optimal when certain process and hardware-wise requirements, are realised on the manufacturing side. We will conclude the chapter with an overview of the framework. Abedin et al. (2014)

## 3.1 Manufacturing processes

A new paradigm shift in the discrete manufacturing world requires a production that is competitive but also sustainable. Most of these solutions lie in the field of Cyber-Physical systems. A Cyber-Physical entity is one that integrates its

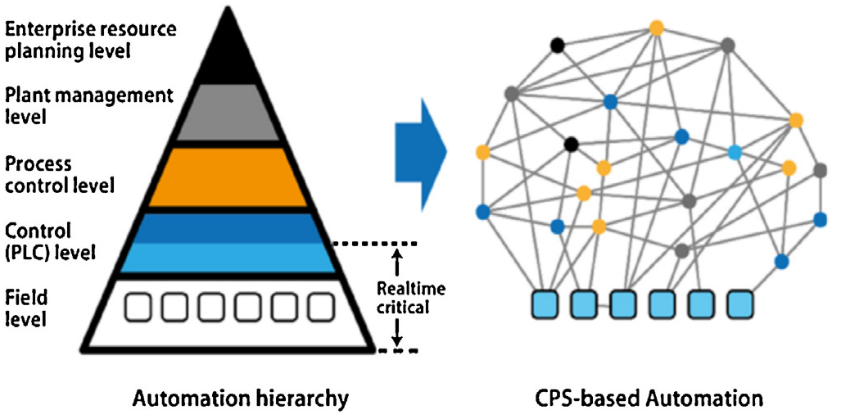


Figure 3.1: The breaking of the traditional automation pyramid, and future of a new more decentralized way of function. Image from Monostori et al. (2016).

hardware with a cyber-representation as a virtual representation. By doing so, it combines two worlds: the embedded systems and the software worlds. By doing so it breaks the traditional automation pyramid, and introduces a new more decentralized way of function (Leitao et al., 2016). This is also visualized in figure 3.1.

The traditional automation pyramid, is very similar to the multiple layers in the manufacturing process, which has been standardised by the American National Standards Institute (ANSI) (Harjunkoski et al., 2009). The integration of the planning and control in the manufacturing process is one that has many aspects. Below a short overview of manufacturing will be given in the ANSI structure. This goes from asset management using process control, to real time monitoring.

### 3.1.1 Asset management

Asset Management is the broad overview of the administration of assets. This includes the design, construction, use, maintenance, repair, disposal and recycling of assets. For most corporations and enterprises, the focus lies on the operational aspects of the assets, due to the fact that asset failures result in production or service delays. Therefore, insufficient asset management on one side results in loss of the asset itself, and on the other side loss due to productions delays and loss of service (Trappey et al., 2013). A lot is currently being researched, for example by Leitão (2009), on asset management, and especially the condition monitoring and prediction are in focus. This is due to the shift from reactive repair work to real-time condition monitoring, prediction, diagnostics and pre-scheduled maintenance. Also, traditional asset management approaches are poorly suited for current equipment failure solutions.

Traditional manufacturing control systems are unable to be sufficiently responsive, flexible, robust and reconfigurable due to the fact that they are built upon

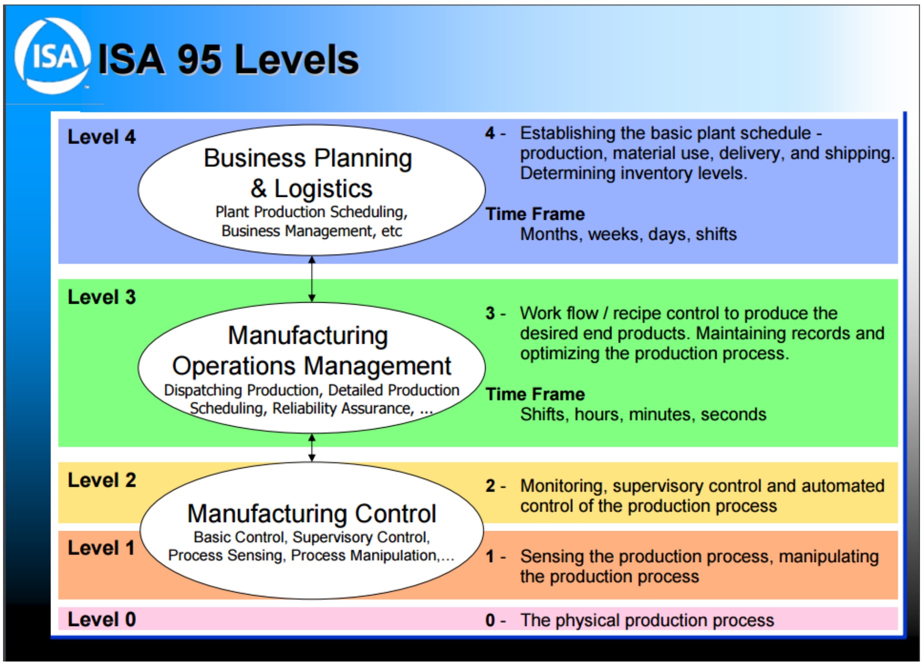


Figure 3.2: The manufacturing levels as described and defined by ANSI for the ISA-95 levels (Brandl and BR&L Consulting, 2008).

a centralised and hierarchical control structures. These are optimal for perfect optimization, but weakly responsive to change. Another consequence of this structure is that a single failure can shut down an entire system (Leitão, 2009). This requires a change to decentralized asset management, demanding for new process control methods.

Generally, researchers use agent-based technology to represent real world situations through the use of a computational simulation process, where agents can interact with each other to find a common goal. Typically, in these environments, agents have conflicting goals. In such circumstances, they will negotiate with each other in order to resolve conflicts (Rosa et al., 2009). These methods will be described in section 3.2.6.

### 3.1.2 Process control

There are three different processing methods: discrete, batch and continuous. Each process can be defined in terms of one or more of these methods. A discrete process method is when the production results in separate pieces. These are for example created in Industrial Robotic Solutions. Each robot produces a separate product in the manufacturing process. It is one of the most used manufacturing production application.

Batch production is when specific quantities of the materials have to be com-

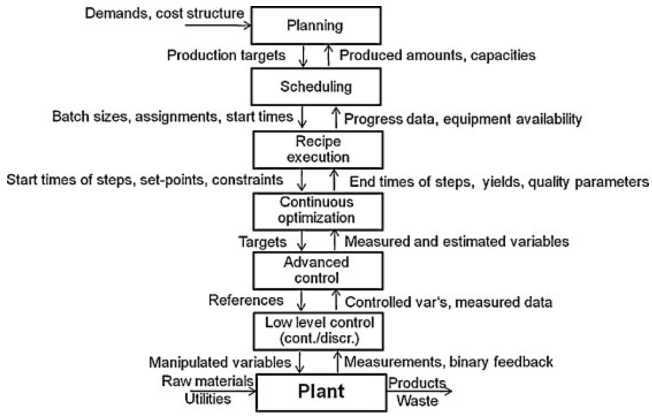


Figure 3.3: Typical process structure from Engell and Harjunkoski (2012)

bined in particular ways. These are typically food productions. An example is the beer production. In a specific batch, the ingredients are combined, and after a period we have our required product. The last process method is continuous production. This type of control is required if the variables are smooth and uninterrupted in time. The process of the creation of de-mineralized water is a continuous process. The water continuously flows through the system and finalizes in the required product with no interruptions.

An example from Engell and Harjunkoski (2012), which is displayed in figure 3.3 shows the typical process control method. This is in line with the ANSI standardisation described in the introduction.

### Planning

Important when controlling a process is to optimize the planning. The forms of decision making used in optimization of planning play an important role in the performance of a production plant. By using different mathematical and heuristic methods, the limited resources can be correctly allocated. This optimization is essential such that the objectives and goals of a company are satisfied (or even better). By minimizing, for example, the time to complete the production, while satisfying the goals, efficiency is increased, which often results in cost reduction (Pinedo, 2005).

One of the largest difficulties when planning, is that of ensuring that the assets are always operational, or have (as short as possible) planned downtime. This is achieved with predictive maintenance.

### 3.1.3 Predictive maintenance systems

To prevent malfunctions, maintenance is necessary. However, this maintenance results in downtime, and is preferably left out, to keep operations running. This however results in the breakdown or wear-out of these systems. By using maintaining assets before they break by so called “preventive maintenance” this damage can be controlled.

The old fashioned model is corrective maintenance. Since maintenance results in the shut-down of production plans, most companies postpone the maintenance to the last moment possible. By ensuring to take as many hours as possible from the machine, the most is taken out of their investment. However, since the breakdown can happen any moment, they need a high inventory of spare parts and materials. And usually the repair is more expensive than maintenance.

Preventive maintenance is the alternative to corrective maintenance. Using predetermined fixed interval planned maintenance, the asset are maintained. However, this results in the not knowing whether maintenance is planned too early, or worse, too late. How can one be assured that the maintenance timing is optimal, due to the many factors of influence on the asset (wrong usage, or external surrounding like sun, dust and rain)? Often either maintenance is done to soon, resulting in extra cost, or to late which results in the breakdown of the asset.

Condition-based maintenance is a step in the right direction. By ensuring preventive maintenance on the right moment, the machines do not breakdown and there is no overkill on maintenance. On specific intervals, the machines are measured regarding their current status and using, for example, vibration measurements or oil samples, their current condition can be assessed. Parts that have a high probability of failure can be replaced in their next maintenance or production stop. However, this is not the optimal solution: measurements are sporadically done (not continuously) and there remains the chance of failure before the maintenance stop has occurred.

Using predictive maintenance it is possible to continuously, in real-time, monitor an installation. This can be done over a distance. Currently there are assets filled with sensors which produce data. This data is shared with people, other machines and servers. This allows for predication of failures, and real-time maintenance.

Currently a lot of research is conducted on this new form of maintenance (Muller et al., 2008). This central analysis is done by recognizing patterns in the data which allows for prediction of possible faults. This branch of maintenance is also known as e-maintenance (Yu et al., 2003), condition-based maintenance or intelligent maintenance (Vermaak and Kinyua, 2007).

### 3.1.4 Real-time Monitoring

To ensure that processes are running accordingly and continuous planning is applied, real-time monitoring is required. Essential in implementing a real-time plan or schedule is that it has to be generated in seconds on the available computer. This may be the case if rescheduling is required many times a day because of schedule deviations. This can be done in two ways. The first way is to review the overall processes and functions performed on the data in real time, or as it happens, through graphical charts and bars on a central interface/dashboard. The second method is by implementing a programmable logic controller. By automating the industrial electromechanical processes, in a predictable and repeating sequence by use of a logic ladder, a real-time controller is achievable.

## Manufacturing with agents

When dealing with multiple processes, production and manufacturing wise, and have to keep real-time track of the assets with sensors, the most common solution lies in agent solutions Leitão et al. (2013); Monostori et al. (2016). This is often easier said than done. In the following section, an introduction in agent-solutions will be given with a focus on negotiation and manufacturing.

## 3.2 Agent Solutions

The new requirements in production ask for new manufacturing planning. This requires a new planning method, which is best implemented using distributed, decentralized structures (Parunak, 1999). The basis of a distributed method lies in Object-oriented programming (OOP) and Multi-Agent structures. Using these structures and negotiations planning can be optimized.

### 3.2.1 Object-oriented programming

Object-oriented programming (OOP) is a programming method based on the concept of "objects", which may contain data and code. For example an object can be a variable, a data structure, or a function, or a combination of these. The code that an object contains can be seen as the behaviour of the object, and as such it is easily interchangeable with an agent, since a method (or message) in OOP is a procedure associated with an object. An object is made up of data and behaviour, which form the interface that an object presents to the outside world (Shoham, 1993).

Agent-oriented programming is a method often used to implement a multi-agent system. In such a system anthropomorphic ideas, like beliefs, desires are used to model the objects, and thus called agents (Shoham, 1993). Agents will be discussed later in this overview.

### 3.2.2 Multi-Agent Systems

Some terms used in the literature for data collection apparatus that aggregate the data are "Smart Objects", "Intelligent Gateways", "Collaborative Network", "Wireless Sensor Network" and "Industrial Agents". Most of these can be viewed as Multi-Agent Systems (MAS) where the sensors communicate with one another as decentralized intelligent agents for independent action performance depending on the context, circumstances or environments (sensor input) of the situation. From such MAS, Ambient Intelligence is conceivable: real-time decentralized decision making based on real-time data acquisition, analytics and negotiations. An example structure can be seen in Figure 3.4.

To define MAS, an agent needs to be defined. An agent is a system that is capable of independent action on behalf of its user or owner. As Wooldridge (2009) formulates it, "An *agent* is a computer system that is *situated* in some *environment*, and that is capable of *autonomous action* in this environment in order to meet its delegated objectives." This independent action execution is already a form of intelligence(Wooldridge, 2009). In the MAS the developer would most probably implement such intelligence by giving each agent "Beliefs, Desires, and Intentions" (Rao et al., 1995).

Multi-agent systems (MAS) have been identified as one of the most suitable technologies to contribute to the deployment of decentralized optimization that exhibit flexibility, robustness and autonomy(Vinyals et al., 2011). Currently there are a lot of relevant contributions regarding agent technologies to this emerging application domain. However, many challenges remain for the establishment of MAS as the key enabling technology (Vinyals et al., 2011). A few problems, like a lack of focus on multiple owners, decision making with only available local knowledge research and lack collective sensing strategies, are still subjects that require extensive research. They see these as the possibly most active MAS research topics. Many of these problems can be solved with negotiation, which will be covered later.

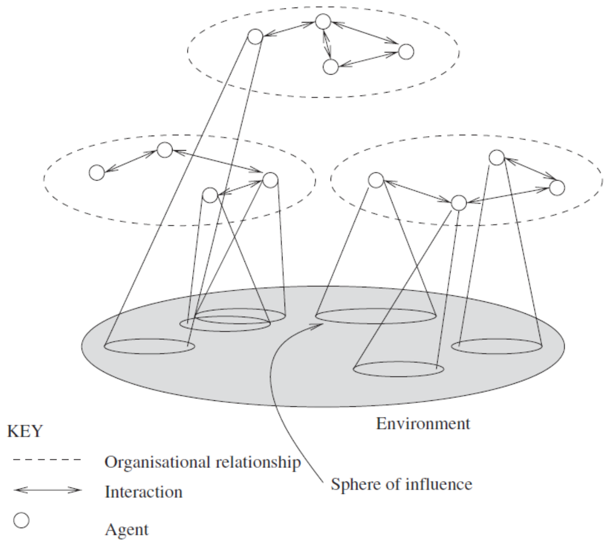


Figure 3.4: Typical structure of a Multi-Agent System (Wooldridge, 2009).

### 3.2.3 Holonic Systems

Multi-agent systems are composed of autonomous software entities *. They are able to simulate a system or to solve problems. In manufacturing the requirement linked to the real-time processes resulted in a new entity and control structure: Holonic systems (Giret, 2005). A holon, just like an agent, is an intelligent entity able to interact with the environment and to take decisions to solve a specific problem. Holon has the property of playing the role of a whole and a part at the same time. The first successfully implemented holonic structure was created by (Van Brussel et al., 1998). PROSA consisted of three types of basic holons: order holons, product holons, and resource holons. They were structured using the object-oriented concepts of aggregation and specialisation. By decoupled the system structure from the control algorithm, logistical aspects could be decoupled from technical ones.

*The holonic structure used in our design will be explained in the chapter 4, including a visualization

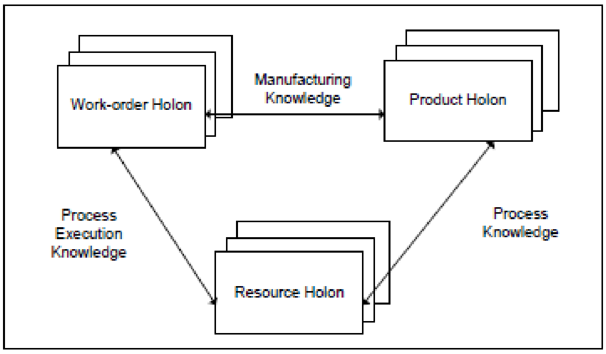


Figure 3.5: An example of an Holonic Manufacturing System (from Giret (2005), based on Van Brussel et al. (1998))

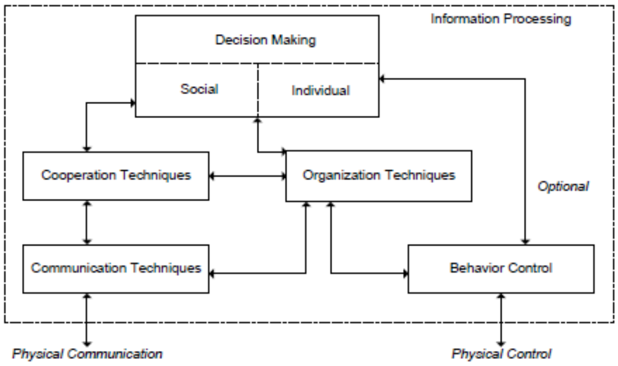


Figure 3.6: An Holonic agent based architecture Giret (2005)

The concept of holon is based on the idea that complex systems will evolve from simple systems much more rapidly if there are stable intermediate forms than if there are not; the resulting complex systems in the former case will be hierarchic. Secondly, although it is easy to identify sub-wholes or parts, wholes and parts in an absolute sense do not exist anywhere (Van Brussel et al., 1998).

### 3.2.4 Task/resource allocation

An example of resource allocation is when a set of agents shares a joint resource. Such a resource can be anything from indefinitely renewed continuous or discrete theoretical resource. By limiting the use of the resource to one agent at the time, negotiation is necessary to ensure that all the agents can use the resource. Usually and often crucial is the preference of the agents. Since the agents have different preferences regarding the resource, it is possible and feasible to divide the resource and create a schedule describing who has access to the resource and when (Fatima et al., 2014b).

The same principle applies to task allocation, where the agents want to achieve a common goal. To achieve this goal quickly the agents most divide different task, which overlap, and reach an agreement on the optimal planning.

### 3.2.5 Scheduling and planning

Since most Process Planning and Scheduling (PPS) problems are NP-hard problems, many MAS have also been deployed to "solve" such problems in reasonable time. NP-hard (nondeterministic polynomial) problems are those problems which are at least as hard as the hardest problems in NP. This means that it is possible to reduce the problems in NP to the original problem in polynomial time. Using the decentralized global optimization approach a (sub-optimal) solution can be found. This solution would be found faster than when using an (mixed) integer program (Feng et al., 2014). It does however depend on the practical application of the system to see whether it is an NP-hard problem. Furthermore, this does not guarantee an optimal solution, rather that a reasonable solution will be found in reasonable time.

Real-world scheduling problems are usually complex and involve many approaches to find sub-optimal rather than optimal solutions using reasonable computing resources. The Bus Maintenance Scheduling Problem (Zhou et al., 2004), which is distributed and dynamic in nature, has received less attention compared to scheduling problems in manufacturing. In the Bus Maintenance Scheduling Problem (Zhou et al., 2004) a MAS is proposed to heuristically solve the bus maintenance scheduling problem investigated here. It is shown that with equal optimality and less computing time without constraint violation it is comparable to the work of a mathematical programming approach.

It is also shown in Bruccoleri et al. (2005) that the agent based approach out performs the centralized mixed integer programming solution for the planning of a production.

Another example is the agile development with a MAS (Rabelo et al., 1999). Agile development is based on the idea that requirements and solutions evolve through collaboration between self-organizing, cross-functional teams. Agile development promotes adaptive planning. By using a MAS for Agile planning, it has been shown that *"the scheduling agility can be extremely improved once it is based on the following key points:*

- *distributed and autonomous systems instead of the centralized and non-autonomous solutions;*
- *negotiation-based decision making instead of the totally pre-planned processes;*
- *application of different problem-solvers in the same environment instead of only one fixed problem solver;*

- *concurrent execution instead of the sequential processing" (Rabelo et al., 1999).*

Each agent is part of a heterogeneous system and processes its own information and has its own particular capabilities that it exchanges to the system. In this matter it contributes to finding a solution to the global problem which works very well in complex environments. Optimization of scheduling in such complex environments is highly constrained, with which advanced analytics also has great difficulty. Using the dynamic, flexible and intelligent relaxation of the constraints within the distributed knowledge of the agents, autonomous intelligent decision making as a Multi-Agent System is achieved (Rabelo et al., 1999).

### 3.2.6 Negotiation

Often discussed above is the negotiation of the agents in a multi-agent system. This branch of research, also called automated negotiation, is studied by Artificial Intelligence and Economics (Jennings et al., 2001). Concepts from fields such as decision theory and game theory can provide standards to be used in the design of appropriate negotiation and interaction environments (Jennings et al., 2001). It is used to reach an agreement that meets the constraints of two or more parties in the presence conflicting interests. And thus is a basic means of getting what you want from others (Fisher et al., 1987). It is back and forth communications designed to reach an agreement when you and the other side have some interests that are shared, and others that are opposed. Agents reason rationally and strategically. An agent's objective is to maximize the expected value of its own payoff.

The four components of a negotiation model are (Fatima et al., 2004):

1. The negotiation protocol.
2. The negotiation strategies.
3. The information state of agents.
4. The negotiation equilibrium.

Since negotiating situations occur when there is a conflict of interest, the first step will be to detect such a conflict. Agents will use communication channels and try to eliminate the conflicts. Conflicts may be about limited available resources, or may be a conflict between the beliefs of some agents. In the first case, optimization is the result, whereas, in the second case, one of the agents will have to change its beliefs (Shen et al., 2003). Often it is seen as maximizing the quality of the result. Two solutions are possible, one, the agents can try to achieve Pareto optimality, meaning that the outcome maximizes the product of the agents' utilities, or they try to reach a Nash equilibrium, meaning an stable state in the system, both which will be discussed in the evaluation method.

Negotiation is done by exchanging messages among agents. Since the process involves several messages, a discussion will take place in which each agent's belief and goals will be an important factor. These depend on the global situation. Clearly, to be able to negotiate, agents must be able to reason. Thus, negotiation is restricted to cognitive agents. Automated negotiation is essentially a distributed search in the space of potential agreements between the different negotiators represented by autonomous agents, which involves the exchange of relevant information and aims to find an agreement that is acceptable to all participants.

Negotiation domains, can be divided into task orientated domains (TODs), state orientated domains (SODs) and worth orientated domains (WODs). TODs are the simplest and an agent's activity is defined in terms of the set of tasks it has to achieve. It is assumed that all resources are available, the benefit of negotiation is the redistribution of tasks amongst a group of agents which results in a more efficient task order. A typical example is mail delivery where an agent may carry another agent's mail at little extra cost. It is sertain that the states come closer to a Pareto optimal solution as all agents can proceed with their original task list and be no worse off. SODs deal with problem where agents wish to change their environment from an initial state to some goal state. The classic AI Blocks World problem is a good example. There is the possibility of conflict and dead end, since the agents may have different goals, and it is not feasible to try and satisfy these goals all for all agents. In this situation, agents must be able to make concessions. WODs are domains where agents attach a worth to each potential state. This allows much more flexible goals to be set and allows concessions to be made on these goals. An example would be agents in an marketplace where the goal for a seller may be to obtain the highest price for x within time y. There is again the possibility of conflict and deadlock, but now within a more complicated bargaining environment (Anumba et al., 2003; Fatima et al., 2014a) .

### Negotiation Protocol

Negotiation Protocol is the set of rules that govern the interaction and defines who are the actors of the negotiation, the states that characterize a trade (for example, when a negotiation has begins or ends), the events that determine the change of actors status, and messages that can be sent by the actors in a particular state. This however is no easy task, since there is no one size fits all solution. Some attempts have been made, by Marsa-Maestre et al. (2014) for example, and a collection of design rules which allow, given a particular negotiation problem, to choose the most appropriate protocol to address it. However, these problems are only derivable when (1) the negotiation domain, including the issues and possible issue values, (2) a scenario utility histogram, which defines the distribution of contracts in utility space, and (3) several structural parameters that specify the topography (e.g. ruggedness) of each agent's utility function are known. In the design of the system, this will be discussed.

The most important protocol is that of the alternating offers protocol. It is based on a divisible pie, discrete or continuous, and is the most widely studied among game-theorist as well as MAS researchers (Fatima et al., 2014b). Other examples is the contract net protocol and the bargaining protocol.

A typical negotiation protocol is very similar to that of our negotiations in our everyday life and work. Thus, a negotiation typically proceeds over a series of rounds, with one or more proposals being made at each round. It also includes the rules that impose the constraints on the rules and the rule that shows when a deal has been struck (Fatima et al., 2014b). Different negotiation mechanisms need to be developed to suit the different application environments of MAS. Unlike the negotiations between human beings which involve more complex human interactions than simple technical issues, the negotiation mechanisms between agents are rule-based or case-based. Yet, the human negotiation approaches and theories, which mainly include game theory and behaviour theory, provide sound bases for the negotiations between agents.

Another common protocol is the monotonic concession protocol. It is a proposal which has also been adapted for multi-lateral negotiation in (Endriss, 2006).

### Negotiation Strategies

The strategy can be defined formally as an apparatus which allows the agent to determine the content of the action that it will perform consistently with the protocol. In general, for a given set of negotiation protocol there are many strategies compatible with it, each of which can determine a different action. This means that a strategy can work well with a given protocol, but does not work with others. So, the choice of strategy depends on the protocol in use and by the trading scenario (Di Nocera, 2015).

Often these strategies are private, meaning that not all the agents can see what the strategy of an agent is (Fatima et al., 2004). Example of a strategy is the Zeuthen strategy which results in the outcomes being equivalent to the Nash bargaining solution.

### Negotiation states

An agents information state describes the information it has about the negotiation game. There are two possibilities, states with complete information and those of incomplete information. The first category is basic and most common. In these games the players are assumed to know all the information about the rules of the game and the players their preferences. However, in the incomplete category, information may be lacking about a variety of factors in the problem

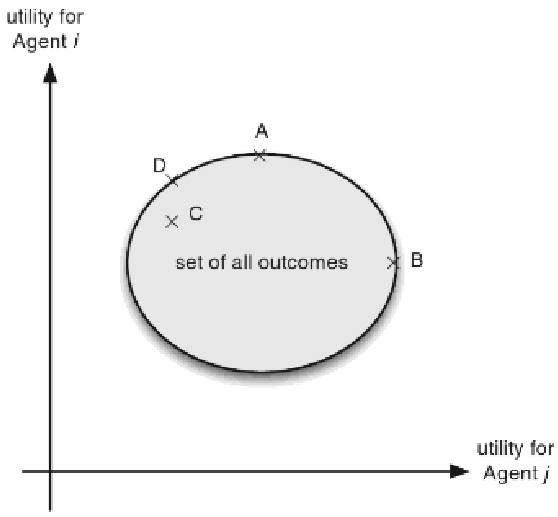


Figure 3.7: An example of Pareto optimal. Locations A and B are optimal, since no improvement, without loss for the agents, is possible. C and D are not optimal. From Fatima et al. (2014b).

**Table 1** Major categories of game theory

| | Static | Dynamic |
|---|---|---|
| Complete information | Static games of complete information: Nash equilibrium | Dynamic games of complete information: Subgame Perfect Nash Equilibrium |
| Incomplete information | Static games of incomplete information: Bayesian Nash equilibrium | Dynamic games of incomplete information: Perfect Bayesian Nash equilibrium |

Figure 3.8: The four types of games in game theory from Trappey et al. (2013).

(Fatima et al., 2004).

### Evaluating /equilibrium solutions

When evaluating the dilemmas of a negotiation between agents essential is the Pareto-Frontier. Visualized in figure 3.7, it is used to determine whether an outcome of a negotiation is efficient. This means that no improvement can be achieved for all agents.

The Nash equilibrium is the best reply to the other players strategies. This means that if both players play their Nash strategy, neither will have the incentive to change their method. Different equilibria are possible and shown in figure 3.8.

### Principled Negotiation

An example of a common method for negotiation is principled negotiation. This method developed by Fisher et al. (1987) was founded on the idea that negotiators could reach better agreements by finding favourable agreements. By focussing on interests not positions and using objective criteria, an agreement is more likely to be reached. This method has successfully been deployed in a Multi-Agent System for air traffic management (Wangermann and Stengel, 1998). Emphasised is the fact that it is important to agree on objective criteria for assessing options (Fisher et al., 1987). If an agreement can be reached using this criteria, it is more likely that it is rational. Furthermore it is useful for systems in which no agent has global knowledge of the system.

The purpose of this type of negotiation is to help to reach agreement without jeopardizing the business relations. It was created by Fisher et al. (1987) and they refer to this kind of agreement as a wise agreement. Wise agreement is agreement that meets the interests of both parties to the extent possible, is long lasting, and also considers the interests of the larger society. The basis of this negotiation principle is to separate the relationship issues from the problem issues, to focus on interests not on positions, while trying to be creative in developing solutions.

### Hierarchy and Voting

Voting is a form of group decision making. The agents participating in the voting will take into account their own preferences as well as those of others when making decision about how to vote. This will often have a strategic flavour. By aiming to rank or order the candidates, a group decision can be made.

Another option are auctions, a popular mechanism to reach an agreement within the allocation of resources to agents. Examples include English auctions, Dutch auctions, Vickrey auctions and First-price sealed-bid auctions (Wooldridge, 2009). Interaction between a large number of low-level agents results in a complex system behaviour which is difficult to understand, to control and to predict. Structuring the agents in a hierarchy is the appropriate solution to tackle this complexity (Van Brussel et al., 1998).

### Mapping of negotiation protocols

An attempt at the visualization of the different negotiation techniques is strived at. Three variables are decided on. Single- vs Multi-Issue negotiation; bi- vs multi-lateral negotiation, and; perfect vs imperfect negotiation.

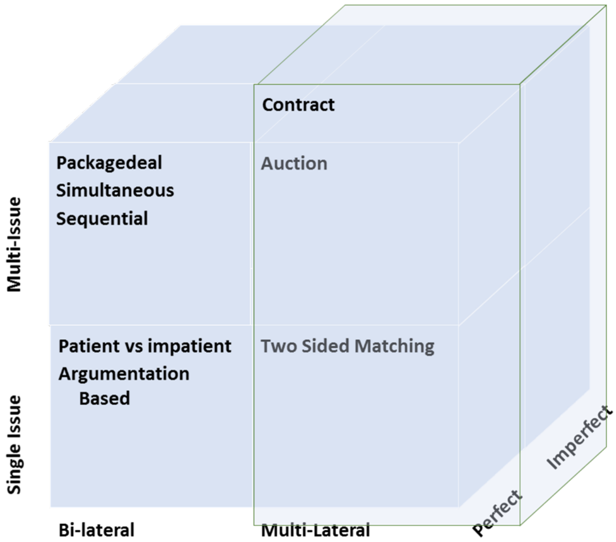


Figure 3.9: Current Negotiation overview

### Single-Issue

Negotiation among self-interested agents has been studied from the perspective of game theory. This is most obvious when the agents negotiate on single issues. An example might be the price of a product. When dealing with a single issue there is only one goal for both agents and there must be a conflict. If there was no conflict, no negotiation would be necessary. Typical single issue methods are patient vs impatient players, two sided matching. Argumentation based methods, which are based on the beliefs of an agents are also included in the mapping.

Essential is that all these methods are a form of the alternating offers protocol. Depending on the sort of players, the method result in completely different behaviours. These negotiation can either be complete or incomplete meaning that all information is known, or not all.

When the game is complete, all the agents know all the information about their states and the strategies of other agents. When not all is known, the game is incomplete. The idea of negotiation is that we have an incomplete game, since if the strategies are known, most negotiation would not be necessary.

When looking at perfect vs imperfect information, it means that either the information states of the agents is perfect, meaning that the agent is perfectly informed of all the events that have previously occurred and actions (like chess), or that not all actions are known. Depending on the implementation of the system, with for example public and private announcements, the difference is made.

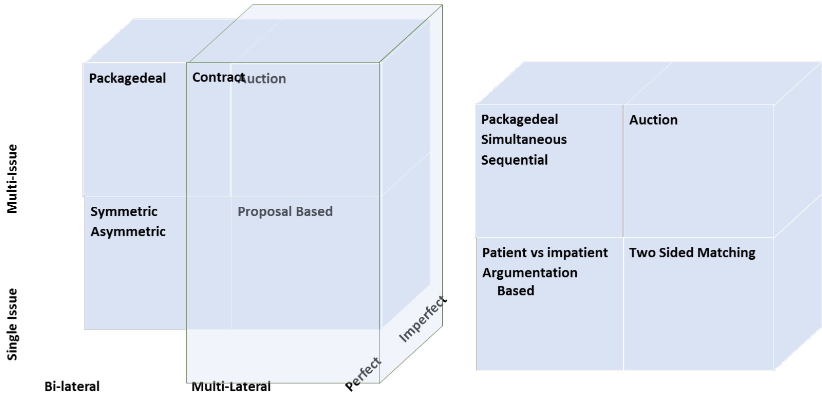


Figure 3.10: Current Negotiation overview

When looking at single issue negotiation, depending on whether the negotiation happens between 2 (bilateral) or more (multi-lateral) agents, there are a few protocols possible. Bilateral negotiation can be either patient or impatient (Fatima et al., 2014a) meaning that an agent has a initiative to limit the time of negotiation. Most negotiation in the manufacturing are time restrained, thus impatient agents must be implemented (Kraus et al., 1995). In symmetric vs asymmetric the players are uncertain about the other players utility functions (as is the case in imperfect negotiation), but essential is that one agent might know more than the other in the asymmetric protocol.

### Multi-Issue

When negotiating multi-issues, agents attempt to combine 2 or more issue in their discussing. An example is the typical seller, buyer relationship between two agents, as for example shown in Schramm and Morais (2013). Here a supply chain construction company is used to asses an method to support bilateral negotiation. Aspects like price, quality and lead-time are considered as issues, on which can be negotiated. Most used multi-issue method, for single-lateral negotiation is the package deal method. In this method, complete packages with all the issues are provided. These can be discussed either sequentially or simultaneously.

Agents can employ either an issue-by-issue (one-at-a-time) approach, or a packaged approach in the negotiation agenda (Fatima et al., 2004). In Abedin et al. (2014) a packaged approach for this is lack of knowledge about the opposing agents. As one issue is settled, the agent subsequently negotiates the other pending issues. This allows the agent to be cautious and opportunistic at the same time. For a multi-issue negotiation under incomplete information settings, the ideal solution is one that is Pareto optimal. A solution is said to be Pareto optimal if no agent can be better off without sacrificing the others utility as will be discussed in the evaluation.

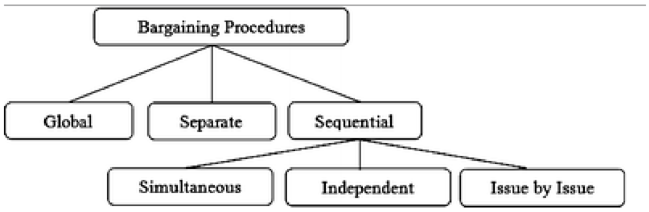


Figure 3.11: An overview of the different negotiation method for multi issues bargaining. From (Abedin et al., 2014).

When choosing the preferred method of negotiation, important to realize is the solution required. As explained above, the issue-by-issue approach has a higher chance of optaining the Pareto optimal solution. Furthermore, the majority of the existing work on multi-issue negotiations focuses on the negotiation strategy, assuming the agenda and the procedure to be predetermined (Fatima et al., 2004; Lai et al., 2004). Interesting to determine would be the influence of the domain and protocol since, depending on the scenario under which the negotiation is taking place a supervised agenda procedure can have a positive impact on the outcome of the negotiation when compared to a procedure without use of an agenda. (Abedin et al., 2014).

**Multi-lateral**

The most common used method for multilateral negotiations are contract based methods, most popular being the contract net protocol. Contract net protocol by Smith (1980) is based on the principle that agents, each with a distinct expertise, can solve sub problems that are required to solve the global problem. This form of cooperative distributed problem solving is based on the assumption that agents in a system implicitly share a common goal, and thus that there is no potential for conflict between them.

Each agent (manager) having some work to subcontract broadcasts an offer and waits for other agents (contractors) to send bids. After some delay, the best offers are retained and contracts are allocated to one or more contractors who process their subtasks. The contract-net protocol provides for coordination in task allocation.

The protocol is best suited to problems in which it is appropriate to define a hierarchy of tasks. Such problems lend themselves to decomposition into a set of relatively independent subtasks with little need for global information or synchronization. Individual subtasks can be assigned to separate processor agents. The main contribution of the contract net protocol is the mechanism it offers for structuring high-level interactions between nodes for cooperative task execution. Negotiation can be used at different levels of complexity. At one extreme, it is a means of achieving task distribution with distributed control and shared responsibility for tasks to maintain reliability. At the other extreme, the twoway transfer of information and mutual selection attributes of negotiation make possible a finer degree of control in making resource allocation and focus decisions than is possible with traditional mechanisms (Smith, 1980).

Since the contract net protocol has the uncertainty of matches being stable, the protocol of two-sided matching has been developed. Furthermore it is not certain that the matches are Pareto optimal. Using the two sided matching method, this uncertainty can be avoided, however, this protocol is harder to implement due to the fact that a clear allocation division is required. (Fatima et al., 2014b).

If the game is imperfect two sided matching does not work, and a proposal based protocol is the right fit (Rahwan et al., 2003).

### Heuristic methods in negotiation

Most of the negotiation in manufacturing can be seen as multi-lateral multi-issue negotiation. Three important distinctions are to be made, based on Lai et al. (2004).

1. issue by issue negotiation;
2. multi-issue cooperative negotiation;
3. multi-issue negotiation with heuristic methods.

The first aspect looks at the agreement which is built through a strategy, and examines this individually and interactively, and the parties are considered as non-cooperative and they are built for environments with incomplete and asymmetric information, where an agenda containing the order in which issues are treated is needed. For the second aspect a multi-issue concession strategy is used whose parties are considered cooperative and they have complete and symmetrical information about their environments. These two aspects have been discussed in the sections above. In the last type, an agreement is reached through a hybrid negotiation strategy, which uses the first two types of theoretical framework with the focus in automated models based on autonomous agents for multi-issue negotiation and in negotiation strategies tractable. This is also where possible learning methods are available (Schramm and Morais, 2013).

These heuristic methods are a lot more common in the implementation of negotiation, as discussed by Leitão et al. (2013); Monostori et al. (2006), since it does not require the through analysis of the states and protocol compared to the game theoretic methods. Also it allows for larger groups and learning in the agents.

Table 1
Negotiation approaches in MAS based on the learning methods

| Approach | Characteristics |
|---|---|
| Probabilistic Decision Theory | Selecting optimal decision |
| Possibilistic Decision Theory | Selecting optimal decision |
| Bayesian learning | Learning negotiation partner's type |
| Possibilistic CBR | Selecting most prospective negotiation partners |
| Constraint-based reasoning | Finding a solution that satisfies constraints of negotiating partners |
| Heuristic search | Determination of negotiation offer |
| Q-learning | Searching the set of potential strategies |
| Evolutionary computing | Searching the set of potential strategies |

Figure 3.12: Overview of different learning methods for heuristic negotiation methods from Beheshti and Mozayani (2014)

**Learning methods in Negotiation**

When dealing with heuristic methods for negotiation, learning methods can be implemented. An overview can be seen in figure 3.12.

Based on the research conducted on heuristic methods and Jennings et al. (2001), it can be concluded that the optimal research in learning in heuristic methods is not yet known. They are often used however to decide on the optimal counter bid in Beheshti and Mozayani (2014). They show that efficient learning algorithms based on an statistical ranking algorithm and linear regression, all with linear time complexities. These characteristics allow our method to be used in real-world applications.

### 3.2.7 Negotiation in Manufacturing

There are many applications of agent based solutions in the manufacturing world (Monostori et al., 2006). In these negotiations an overwhelming aspects is realised in the creation of intelligent individual agents, and less on the overall intelligence of the system. Often ignored is the specific negotiation method in these systems. This is where the problem lays, since conflicting interest, essential in the optimal decision making are left out. An example where these conflicting interest are well implemented is in Zheng et al. (2014). A cloud consumer usually prefers a high reliability, whereas a cloud provider may only guarantee a less than maximum reliability in order to reduce costs and maximize profits. If such a conflict occurs, a Service Level Agreement cannot be reached without negotiation. Automated negotiation occurs, when software agents negotiate on behalf of their human counterparts. However no learning occurs.

Rockwell Automation uses agents in its automation processes and is one of the industrial leaders in the implementation of agent based solutions (Vrba et al., 2011). One of their future insights in the requirements of agent based solutions is to enhance the capabilities of agents for expressing and exchanging knowledge, and as a consequence, to increase the flexibility of control systems. In order to correctly do so, better insights in the negotiation is needed.

Overall, nearly all factory scheduling negotiations use some form of these market-based approaches (Monostori et al., 2006) to implement the solutions. Different version of the contract net protocol were used or other auction based methods. The problem with these methods is that no reasoning about another's interest and desires is achievable. If this is known, more efficient and better systems can be achieved. It is however shown in Bruccoleri et al. (2005) that the agent based approach using market auctions out performs the centralized mixed integer programming solution. This system uses bilateral simultaneous negotiation on the medium level of the production plant. It is however a form of auctions, where the agents simultaneously bid towards the goal. If this system already outperforms a centralized system, a non-auction based method might outperform even better.

Other examples of negotiation in a Multi-Agent System have been deployed in Smart Grids for optimal energy delivery (Pipattanasomporn et al., 2009), the collaborative design of light industrial buildings (Anumba et al., 2003), negotiation in an electronic market of water rights, and for example in the scheduling of Agile software development (Rabelo et al., 1999).

From the above, in comparison with the knowledge obtained, there are two gaps. Firstly, little multi-issue multi-lateral strategic (game theory wise) application have been implemented. An example from the theory is Wu et al. (2009) where a Pareto-optimal-search method for three-agent multilateral negotiation is developed. This however has not been implemented in any real usecase, and would be very interesting to implement. The other gap in the literature is the research into the optimal learning methods for heuristic methods. In de la Hoz et al. (2015) a wireless surveillance sensor networks is optimized using heuristic learning methods. This is limited to a bilateral negotiation protocol with a mediator, where negotiating agents (two access providers, each of them controlling a fraction of the access points in the scenario) negotiate. No multilateral application has been attempted. An attempt at generalizing multilateral heuristic learning has been made in Beheshti and Mozayani (2014), but this has not been applied to a real use case as of yet.

The last option, an application of multilateral heuristic learning, is the best fit on the usecase.

# Chapter 4

# Research Design & Application

As discussed in the literature review this research has a focus on the negotiation of the agents. Using different methods and techniques an attempt is made to optimize a production process. We search for an approximate-optimal solution while the optimal solution is unknown. Based on learning methods from decentralized holonistic methods, utility and negotation domains a simulation can be build which can be applied to the production process.

The system where the decentralized solution will be applied is a de-mineralized water plant as described in the introduction and problem chapters (chapter 1).

As explained in the literature, a negotiation problem can be characterized by a negotiation domain (who negotiates and what to negotiate about), an interaction protocol (which rules govern the negotiation process) and a set of decision mechanisms or strategies that guide the negotiating agents through every phase of the interaction protocol Fatima et al. (2014b).

For the scope of this work, we assume a multi-attribute negotiation domain, where a deal or solution to the problem is defined as the set of attributes (issues), and each one of them can be in a certain range.

The coding will be done in Java from scratch. Multiple open-source systems area available, including Jadex, which is perfect for communication research in a Multi-Agent System Kravari and Bassiliades (2015). However since most of these systems are very comprehensive little adjustments which are necessary for our research are not conceivable.

## 4.1 Mapping of Literature on usecase

| | Category | Literature | | Usecase |
|---|---|---|---|---|
| Real-time | Physical (process) | Object/service oriented programming | | Operations:<br>• Production Guarantee (leveringszekerheid)<br>• Batch Production<br>• Ions, flow, Ammonia (water softening) |
| Real-time | Sensing | Programmable Logic Controller; Real-time Monitor | Negotiation Holonic, Cyber-Physical | Sensors (mineral, temperature, softening, ammonia, flow) |
| Sec - Min | Analysis | Agent; BDI; Data Analysis; Machine Learning | | Predictive/Condition based Maintenance |
| Hours - Weeks | Work order/Action | Planning; MAS; Scheduling; Game Theory | | Work flow; Logisics Spare Parts; Process control feedback; integrated supply chain |

## 4.2 Demineralization of water

As discussed in the introduction, the usecase where an Multi-Agent system for production will be implemented is a water demineralization plant. An application of this new model will be applied to a large plants that creates demineralized water. By removing all the ions from common water, de-mineralized water is obtained. This water is used for many processes, and has many applications. In this plant specifically it is used for the steam turbines, which generate electricity. By burning the by-product, heat is generated, which creates steam to power the turbines.

Minerals are removed from water by multiple production steps. Most common,

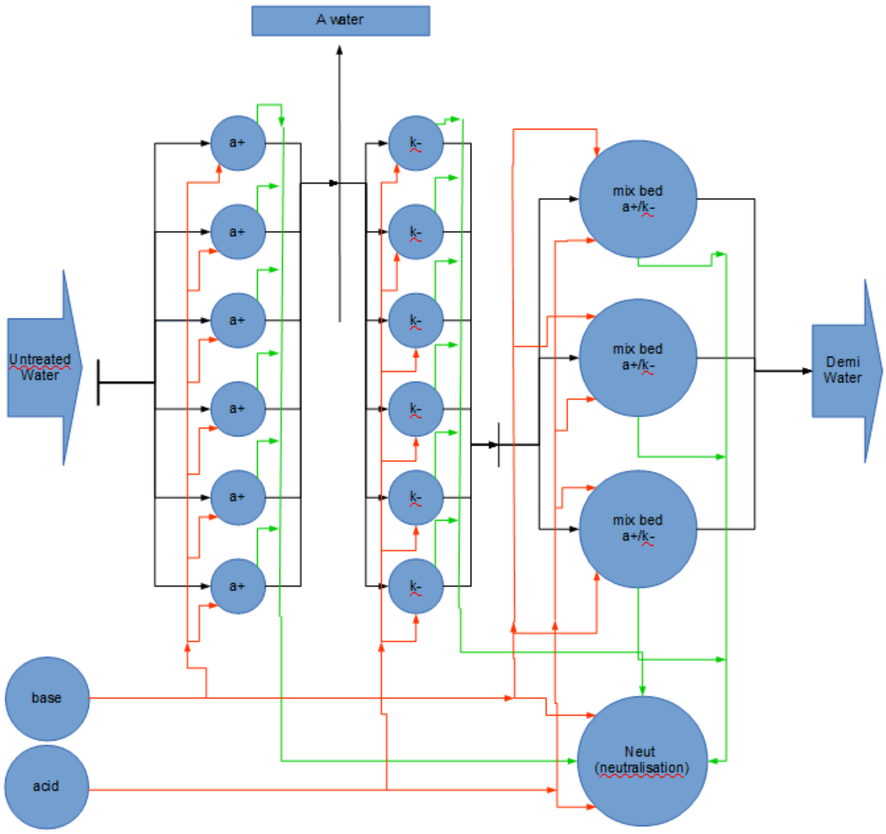


Figure 4.1: An overview of the water demineralization plant.

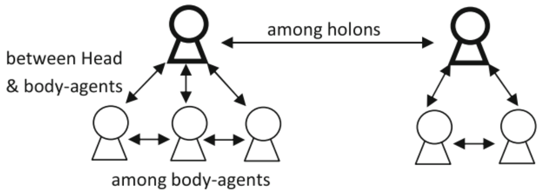


Figure 4.2: An example of the different negotiation between holons from Beheshti et al. (2016).

and as is implemented in the plant described, is to first remove the positively charged minerals in so called anions. After this the negative charged ions are removed with in a cation filter. To ensure all ions are removed, a final combined "mixbed" is used. Here a combination of an anion and cation filter removes the residues.

These filters have to be cleaned every few hours to ensure proper demineralization occurs. For cleaning acid and base are used. By filtering the anion with base the ions that have been retrieved in the filtering are flushed. The residue, still of a base composition, is stored in a storage tank where the combination of the base and acids from the filters is neutralized. This storage tank is called the "Neut" as short.

So overall we have 4 kinds of filters, the anions, the cations, the mixbed and the Neut. Each of these filters sorts have multiple of each other, but for simplification we only look at the allocation of resources for these four "agents". Within each agent the BDI module will ensure the right task location. This will not be done with negotiation but with the BDI which is retrieved from the experts knowledge.

This structure is that of a holon as can be seen in figure 4.2. As shown in the literature it is based on PROSA by Van Brussel et al. (1998).

## 4.3 Negotiation model

These 4 rational agents, $N = \{1, 2, 3, 4\}$, partition 3 issues $M = \{1, 2, 3\}$: the water that has to be delivered at the end of the process, and the base and acid for cleaning. This can be simplified to a buyer seller negotiation.

Anion wants to buy as much base as possible, while the minimum amount of water. For the cation, as much acid as possible is required, while still as little water as possible should be produced. The mixbed requires as much as possible acid and base for cleaning. Since it the final production step, it requires the water to be delivered, forcing it to obtain as much water as possible from the

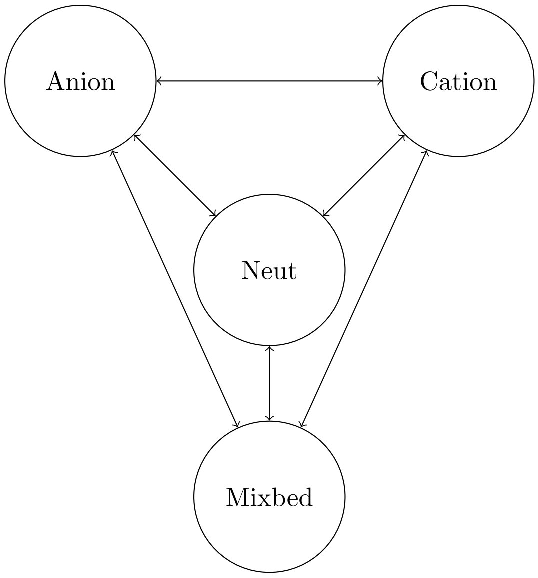

Figure 4.3: A simplified representation.

cation. Finally there is the Neut which wants as little base and acid as possible. Also the base and acid should be levelled out as much as possible to attempt to stay as close to a pH of 7

The protocol is based on the method as proposed by Wu et al. (2009). Here an multilateral multi-issue method for negotiation about the allocation of resources is given.

Since the agents have no knowledge regarding the states of the other agents each agent will have its own utility function.

The negotiation takes place in rounds $n \in \mathbb{N}$. $\mathbf{x}_i \in (0,1)^2$ denotes a bid of agent $i \in N$ in a round and $x_{i,j} \in \mathbf{x}_i$ denote the amount of issue $j \in M$.

Using BDI in each agent, the anion will know which filter to use when, and when to clean them. This intelligence can be learned. There is a limit on the amount of water, base or acid.

Head tries to increase the holon utility as a whole, and this does not contradict the increase in body-agent utility. In other words, Head wants to increase holons utility, and is willing to do this according to body-agent preference.

## 4.4 Details of the Agents

Each agent has its own characteristics on which the system will run. The basis consists of the different sub agents. The head agent will know the state of the

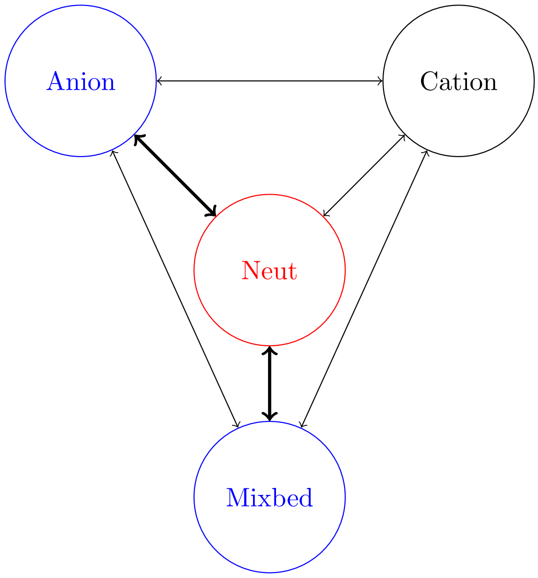


Figure 4.4: Base negotiation. Red indicates seller, blue buyer

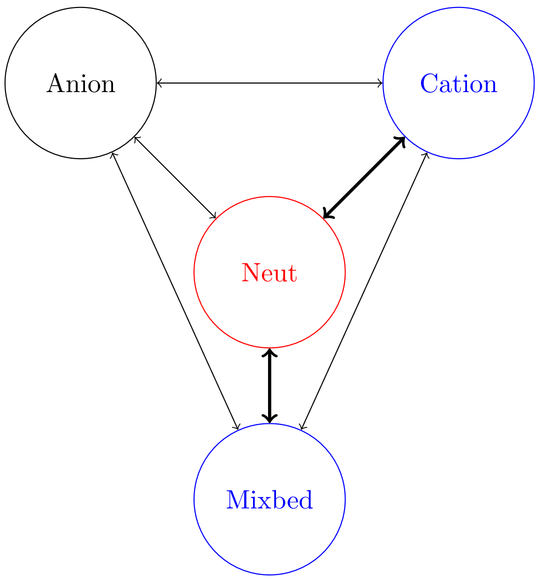


Figure 4.5: Acid negotiation

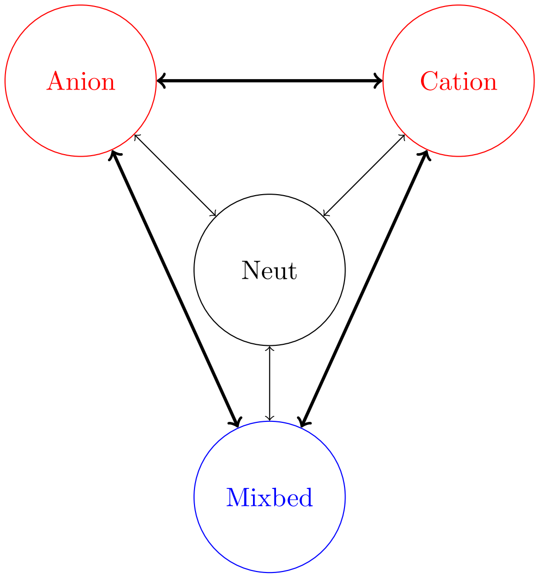


Figure 4.6: Water negotiation

sub agents and will negotation on heave of the entire group.

### 4.4.1 Anion

The anion is the first filter where the untreated water will arrive. The filters have different charatistics and it is the job of the head to decide on the filters task. SOme will be pauzed, some will filter, and others will be cleaned.

#### Utility function

As described in Wong and Fang (2010), it is possible by combining the input into the utiltiy function of the agent. This is shown in fig. 4.7.

At first a simple linear utiltiy function will be used: the less water, the higher the utility. Also, the more base, the higher the utility. This has a limit, depending on the reservation function as shown in section 4.4.1.

A very important input to the utility function is that of the belief in the other agents. These will not be formally modelled, as in Kripke worlds e.g., but can still be used as input to the utility function.

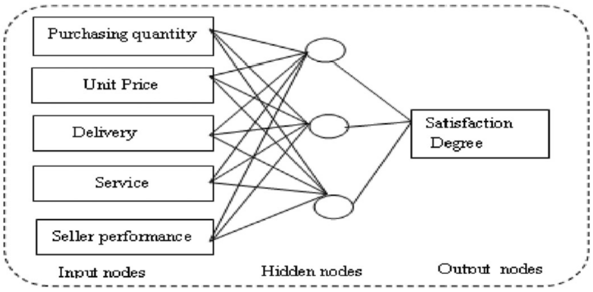


Figure 4.7: An example where the utility function is modelled with a Neural Network. (Wong and Fang, 2010).

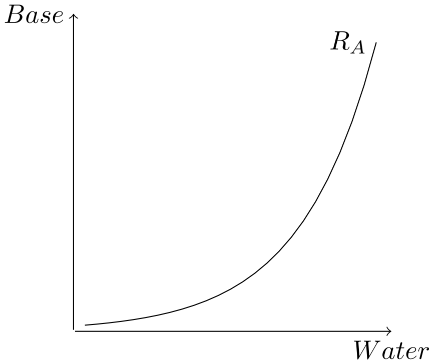


Figure 4.8: The reservation function for the Anion filter: the more water is filtered and given, the more base it requires.

**Facts**

The following facts and rules are part of the Anion.

1. Knowledge of anion head about the sub-agents:
   - $\{A_1, ..., A_6\}$ can process $a$ amount of water
   - $\{A_1, ..., A_6\}$ needs to be cleaned after $b$ water
   - $\{A_1, ..., A_6\}$ has filtered $c$ amount of water
   - $\{A_1, ..., A_6\}$ needs $d$ base to clean
   - $\{A_1, ..., A_6\}$ needs $e$ time to clean
2. Currently $x$ amount of water being filtered
3. Currently $Z \subseteq \{A_1, ..., A_6\}$ filter being used for water filtering
4. Currently $Y \subseteq \{A_1, ..., A_6\}$ filter being used for cleaning
5. Currently $w$ amount of base being used for cleaning

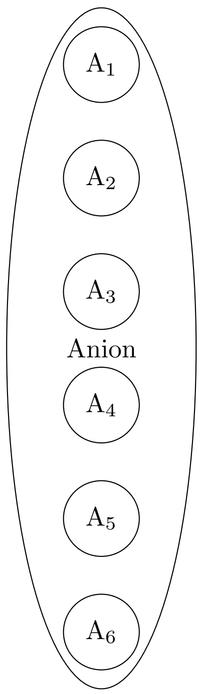


Figure 4.9: Anion head and sub-agents

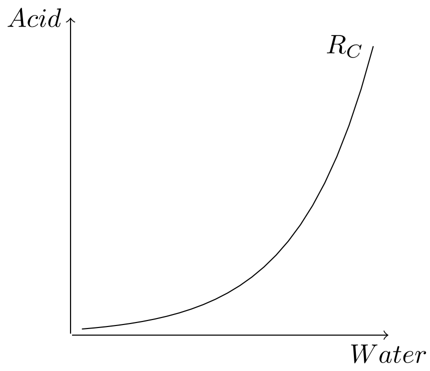


Figure 4.10: The reservation function for the Cation filter: the more water is filtered and given, the more acid it requires.

### 4.4.2 Cation

The cation is the second aspect of the water cleaning process and where the positively charged ions are removed. It cleans itself with acid. A overview of the filter is shown in fig. 4.11.

The utility is very similar to that of the Anion but a preference over acid instead of base is required. The reservation function is shown in section 4.4.2.

**Facts**

The following facts and rules are part of the Anion.

1. Knowledge of cation head about the sub-agents:
   - $\{C_1, ..., C_6\}$ can process $a$ amount of water
   - $\{C_1, ..., C_6\}$ needs to be cleaned after $b$ water
   - $\{C_1, ..., C_6\}$ has filtered $c$ amount of water
   - $\{C_1, ..., C_6\}$ needs $d$ acid to clean
   - $\{C_1, ..., C_6\}$ needs $e$ time to clean
2. Currently $x$ amount of water being filtered
3. Currently $Z \subseteq \{C_1, ..., C_6\}$ filter being used for water filtering
4. Currently $Y \subseteq \{C_1, ..., C_6\}$ filter being used for cleaning
5. Currently $w$ amount of acid being used for cleaning

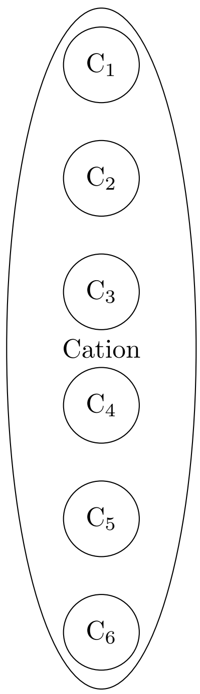

Figure 4.11: Cation head and sub-agents

### 4.4.3 Mixbed

The mixbed is where the final cleaning occurs (see fig. 4.12). It is also the agent responsible for the end water delivery. Since it consists of a mixture off anion and base it has three issues it desires. These are shown in section 4.4.3 and **??**.

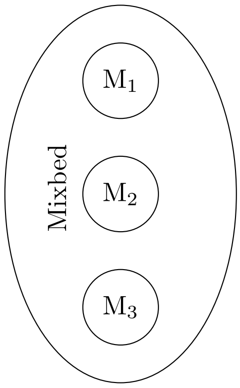


Figure 4.12: Mixbed head and sub-agents

#### Facts

The following facts and rules are part of the Mixbed.

1. Knowledge of anion head about the sub-agents:
   - $\{M_1, M_2, M_3\}$ can process $a$ amount of water
   - $\{M_1, M_2, M_3\}$ needs to be cleaned after $b$ water
   - $\{M_1, M_2, M_3\}$ has filtered $c$ amount of water

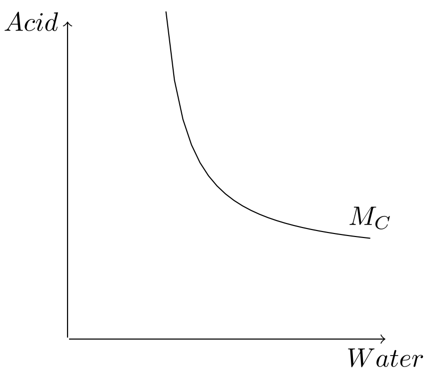


Figure 4.13: The reservation function for the Mixbed filter: a bear minimum of water is required at all times, and thus a bare minimum of cleaning acid.

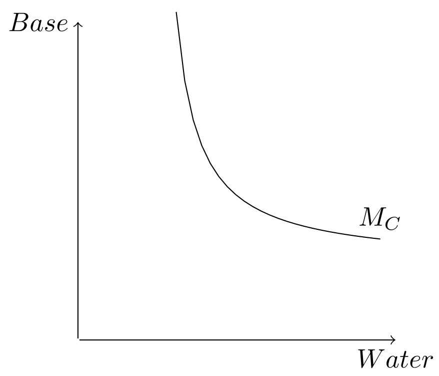


Figure 4.14: The reservation function for the Mixbed filter: a bear minimum of water is required at all times, and thus a bare minimum of cleaning base.

- $\{M_1, M_2, M_3\}$ needs $d$ base to clean
- $\{M_1, M_2, M_3\}$ needs $e$ time to clean
- $\{M_1, M_2, M_3\}$ needs $f$ acid to clean

2. Currently $x$ amount of water being filtered
3. Currently $Z \subseteq \{M_1, M_2, M_3\}$ filter being used for water filtering
4. Currently $Y \subseteq \{M_1, M_2, M_3\}$ filter being used for cleaning
5. Currently $w$ amount of base being used for cleaning
6. Currently $v$ amount of acid being used for cleaning

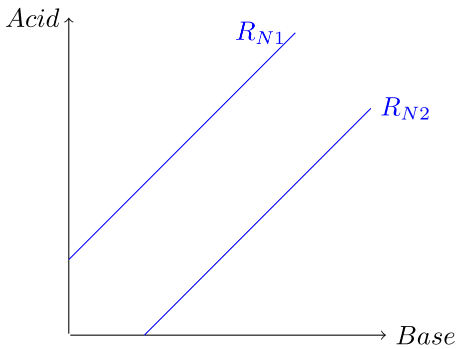


Figure 4.15: The neut reservation curve. A near equal division is required.

### 4.4.4 Neut

The neut is the agent responisble for the division of the amount of Acid and base. Since it wants to stay as pH neutral as possible, it requires an even distribution of base and acid between the agents. This is shown in fig. 4.15.

#### Facts

The following facts and rules are part of the Neut.

1. Current $a$ amount of acid being used.
2. Current $b$ amount of base being used.

## 4.5 Evaluation

Data from a true demi plant is used to see wether the solution will be optimized.

## 4.6 Algorithm

**Data:** Each agents utility function $u_i(x)$, reservation utility $ru_i$, and concession strategy $s_i(t) = 1, 2, ..., T$
**Result:** Negotiation Agreement
initialization: Each agent proposes a preferred offer $x_0$;
$t \leftarrow 1$;
Set convergence tolerance: $\delta$;
**while** $t \leq T$ *and Isconverge == False* **do**
    Determine the agent to propose: i = mod(t,m);
    **foreach** $j \in 1, 2, ..., m$ **do**
        **if** $j == 1$ **then**
            Agent $i$ concedes by determining $s_i(t)$;
            Agent $i$ calculates: $w_{t-1} \leftarrow \frac{1}{m} \sum_{j=1}^{m} x_{t-1}^{j}$;
            Agent $i$ proposes $P_{A_t^i}[w_{t-1}]$;
        **else**
            $x_i^j \leftarrow x_{t-1}^j$;
        **end**
    **end**
    **if** $\max_{j \in 1,2,...,m} \parallel x_t^j - w_{t-1} \parallel < \delta$ **then**
        IsConverge $\leftarrow$ True;
    **else**
        $t \leftarrow t + 1$;
    **end**
**end**

**Algorithm 1:** Basic algorithm structure from Zheng et al. (2015).

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