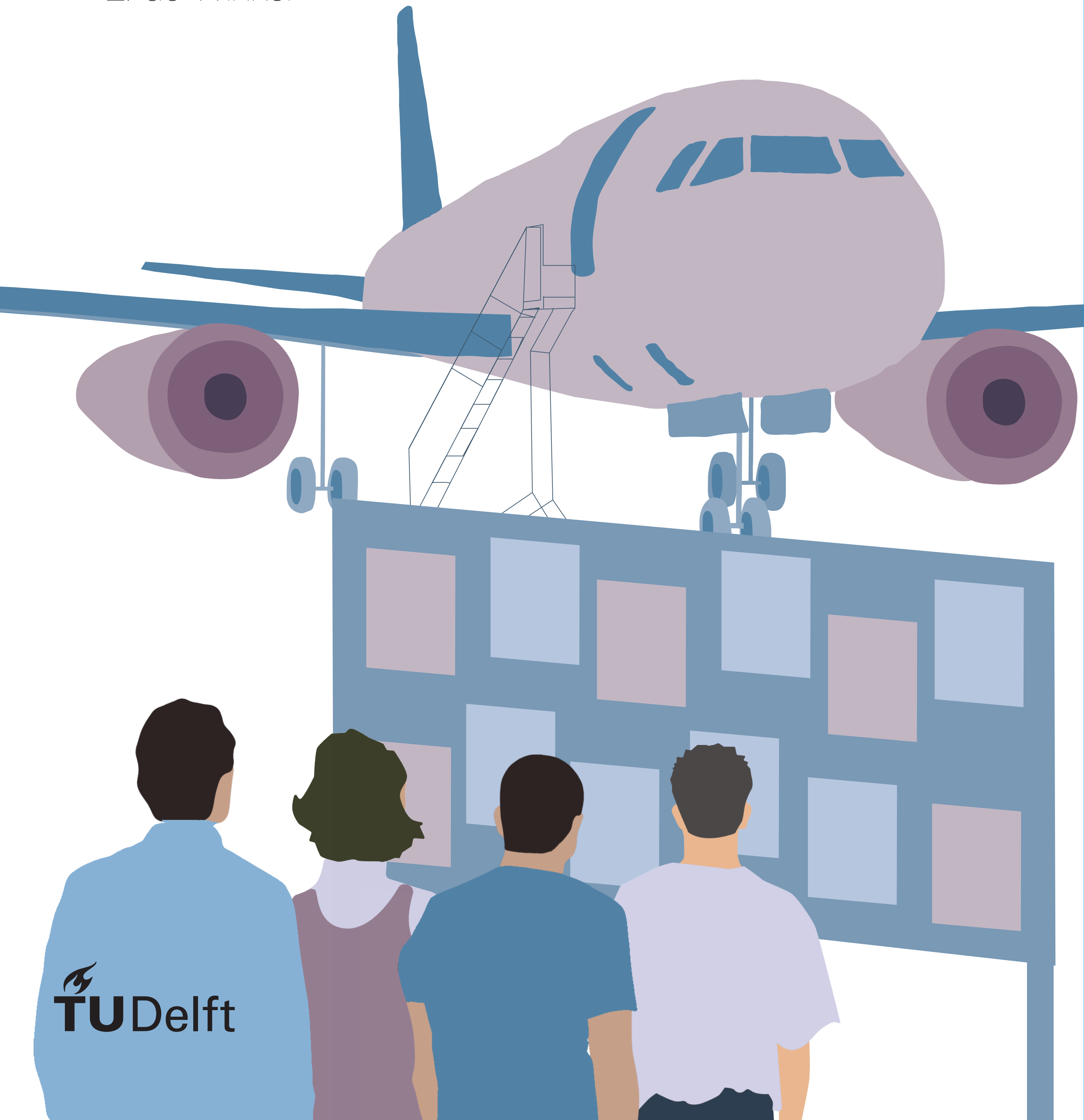
An Agent-Based Social Simulation Approach to Task Allocation in Aircraft Maintenance Teams

Master of Science Thesis

E. de Winkel



TUDelft

An Agent-Based Social Simulation Approach to Task Allocation in Aircraft Maintenance Teams

Master of Science Thesis

by

E. de Winkel

To obtain the degree of Master of Science in Aerospace Engineering
at Delft University of Technology.

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Preface

This thesis reports on my research for obtaining a Master of Science Degree in Aerospace Engineering at Delft University of Technology. This research project focuses on my sincere interest in socio-technical systems. Researh into socio-technical systems aims to increase our understanding of the relationship between humans and technology, which is of striking importance in the present digital age.

This research has for sure been the most educational part of my studies. It provided me the opportunity to learn more about social science as well as agent-based modeling techniques in particular. This would have, however, never been possible without my supervisor's, Dr. Alexei Sharpanskykh, support. I would like to express him my gratitude for sharing his knowledge and insights, as well as personal guidance and inspiring conversations about human behavior and the socio-technical systems we encounter in our daily lives. Moreover, I would like to thank Dr. Soufiane Bouarfa and Dr. Reyhan Aydogan, which were so kind of to share their expertise and answer all of my questions along the way.

Thank you to all my ATO friends for making the long hours of work during the master program a lot more bearable. Thanks Jeanette, Laurance, Olivier, Wouter and all others for these moments together. Moreover, I would specially like to thank my boyfriend, Baginda, who made sure that I would disconnect from all the work occasionally. Moreover, I want to thank my little sisters, who, both in their own ways, have the gifts of making all my seemingly big problems feel very small. Finally, I would like to thank my parents, Jacqueline and Hans, for their unlimited support during my studies, and for guiding me through the process of becoming an adult from the day they drove me to Delft until the very present.

This research concludes almost seven years of my life as an Aerospace Engineering student at Delft University of Technology. Fortunately, I've had many opportunities of broadening my horizon, both outside and within the university. I feel like I've explored all different areas on campus, each remembering me of another phase within my studies. Delft has been part of my identity and, although I've been waiting for this moment for such a long time, saying goodbye has never been my best quality. Unfortunately I could not perform the last part of my research with my friends on campus due to the current Corona crisis. But I guess the good thing is, that I do not have to say goodbye yet and have a reason to come back later after all.

E. de Winkel
Delft, April 2020

Contents

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List of Symbols

A_{12}	A-test value comparing algorithm 1 and 2
cl_{ki}	Closeness of agent k and i
cs_i^t	Agent i's belief about the current shift at time t
ct_i^t	Agent i's belief about the current team at time t
$dem(\phi)_{i,f}^t$	Agent i's belief on task f's demand for aspect ϕ at time t
dep_f	Normalized number of tasks dependent on task f in the scheduled shift
$ef_{eff_i}^t$	Agent i's efficiency effort at time t
$ef_{tho_i}^t$	Agent i's thoroughness effort at time t
$efi_{f,i}^t$	Agent i's efficiency effort influence task f's task execution time at time t
etp_i^t	Agent i's experienced time pressure at time t
F_p	Number of tasks in task package p
$goal_i(au)$	Agent i's autonomy goal
$goal_i(eff)$	Agent i's efficiency goal
$goal_i(es)$	Agent i's esteem goal
$goal_i(mas)$	Agent i's mastery goal
$goal_i(re)$	Agent i's relatedness goal
$goal_i(tho)$	Agent i's thoroughness goal
h	Simulation time step in hours
$Imp_{i\to j}^t(\phi)$	Agent i's impression of agent j on issue ϕ at time t
$Imp_{i\to q}^t(T_{q\to i}(\phi))$	Agent i's impression of team q's trust in agent i on aspect ϕ at time t
m	Data set size algorithm 1 for A-value calculation
$mech_f$	Number of mechanics needed for task f
mh_f	Number of man-hours scheduled for task f
mhr^t	Ratio of man-hours of the remaining tasks over the total number of man-hours at time t
N	Number of agents within team q
n	Data set size algorithm 2 for A-value calculation
nde_f	Number of tasks (indirectly) dependent on the completion of task f
o	Task allocation option
$o*^t$	Chosen task allocation option at time t

$p_{f,i}^{t}$	Part of task f that has been finished by agent i at time t
$pe_{i\to j}^{t}(\phi)$	Agent i's perception of agent j on aspect ϕ at time t
q	Agent i's team
$R_{i\to j}(\phi)^{t}$	Agent i's reputational view of agent j on aspect ϕ at time t
$R_{I\to j}(\phi)^{t}$	Group I's reputational view of agent j on aspect ϕ at time t
$R_{i\to J}(\phi)^{t}$	Agent i's reputational view of group J on aspect ϕ at time t
$R_{I\to J}(\phi)^{t}$	Group I's reputational view of group J on aspect ϕ at time t
R_1	Ranksum of data samples 1 and 2 for A-value calculation
shc_i^t	Agent i's belief about whether a shift change is happening at time t
sk_i^t	Agent i's skill level at time t
sk_f^{req}	Skill level required for task f
$ski_{f,i}^t$	Agent i's skill influence task f's task execution time at time t
$T_{i\to j}(\phi)^t$	Agent i's trust in agent j on aspect ϕ at time t
$T_{i\to j}(\phi(p))^t$	Agent i's trust in agent j on executing task package p in line with aspect ϕ at time t
tax_i^t	Agent i's individual Clarke tax at time t
tax_{Ii}	Agent i's group tax at time t
$thi_{f,i}^t$	Agent i's thoroughness effort influence on task f's execution time at time t
tho_f^{req}	Thoroughness level required for task f
$timer^t$	Ratio of the remaining time at time t over the total shift time
tp_i^t	Team lead i's belief about the current task packages
$u_i^t(o*)$	Agent i's utility for the chosen task allocation option
$V_i^t(o)$	Agent i's valuation of task allocation option o at time t
w_{iI}	The weighted mean of agent i's power influence within group I
w_{ji}	The weighted mean of agent j's power influence on agent i
α	Risk aversion factor in Prospect Theory
β	Constant compensating for group size in Dynamic Theory. of Social Impact.
γ_{ji}	Power influence of agent j on agent i
λ	Loss aversion factor in Prospect Theory
μ	Mean
σ	Standard deviation
ϕ	Agents' competence aspect, either efficiency, thoroughness or skill
ω_q	Multiplication factor for theory of mind influences on agents' efforts in team q

List of Abbreviations and Acronyms

ABMS	Agent-Based Modeling and Simulation
ABSS	Agent-Based Social Simulation
ALL	Allocation Outcome Check
DAI	Distributed Artificial Intelligence
DSS	Decision Support System
EASA	European Union Aviation Safety Agency
ICAO	International Civil Aviation Organization
KPI	Key Performance Indicator
MECH	Mechanic
MF	Mediated Feedback Based Protocol
MH	Man-Hours
MLG	Main Landing Gear
MRO	Maintenance, Repair and Overhaul Organization
NSS	Negotiation Support System
NTA	Number of Tasks Finished
SA	Situation Awareness
SAF	Number of Safety Incidents
SC-COM	Compliant Team Scenario
SC-IND	Independent Team Scenario
SC-NEW-1	One New Team Member Scenario
SC-NEW-3	Three New Team Members Scenario
SC-SHIFTS	Multiple Shifts Scenario
SC-SOC	Social Team Scenario
TAS	Absolute Task Execution Time
TIM	Total Execution Time
TL	Team Lead
USW	Utilitarian Social Welfare
VO	Voting
XAI	Explainable Artificial Intelligence

I

Thesis Paper

An Agent-Based Social Simulation Approach to Task Allocation in Aircraft Maintenance Teams

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Tighter profit margins and rising aircraft complexity are currently driving the need for aircraft maintenance organizations to increase efficiency. Many organizations believe that digitization is key for improving operational performance. Digitization of the task allocation process at a large aircraft maintenance organization did unexpectedly not lead to increased efficiency. Anthropological research concluded that the implemented technologies did not accommodate for the social nature of teamwork. This research studies the relationship between the social aspects of teamwork and the performance of task allocation methods in aircraft maintenance. An Agent-Based Social Simulation model has been created and simulated for different types of task allocation methods as well as different types of teams. The presented model includes social influence relations between team members and decision-making based on trust in others' performance. The model has been simulated for a case study of an Airbus A310 main landing gear replacement. Independent teams provided the best performance using a mediated feedback automated negotiation method. The most beneficial results for compliant teams were obtained through task allocation by the team lead. Social teams presented significantly better results for voting than for other task allocation methods. The combination of socially oriented mechanics and task allocation by voting provided the most advantageous task execution performance for all simulations. It was shown that, in line with the wisdom of crowds theory, diversity in initial trust levels in combination with shared trust among mechanics over time increased collaborative task allocation performance.

Agent-Based Social Simulation | Task Allocation | Aircraft Maintenance | Teams | Voting | Automated Negotiation | Agent-Based Modeling & Simulation

1. Introduction

Digitization is currently one of the main aspirations of many large organizations. It is no surprise that in the increasingly competitive airline industry, digitization has been airlines' key focus in order to enhance their operational efficiency [1]. Only recently, tighter profit margins in combination with rising aircraft complexity drove the need for aircraft maintenance organizations to uplift their operations as well [2].

The introduction of new technologies at a large aircraft maintenance organization did unexpectedly not increase efficiency [3]. Anthropological research concluded that the implemented technologies did not accommodate for the social nature of the maintenance work [3]. In particular, one of the mechanics in this research emphasized how helpful it is to know who to trust with certain tasks [3]. He explained the importance of working with a team that fits him best: he knows how others think and what they will take extra notice of [3]. Hence, "teaming" is a fundamental characteristic of the aircraft maintenance work [4]. As a response, the mechanics at the aircraft maintenance organization created their own democratic planning systems to accommodate for collaborative decision-making. The organization was, however, hesitant to adopt the improvised democratic systems.

The anthropological study suggests that the social nature of aircraft maintenance teams impacts the performance of planning systems [3]. Understanding the relationship between teamwork and the performance of planning mechanisms could therefore assist aircraft maintenance organizations in adopting appropriate decision-making protocols. Yet, no research has been performed on studying these relations.

This research sets out to investigate the relationship between the social aspects of teamwork and the performance of task allocation methods in aircraft maintenance. We focus on task allocation, because of its essential role in the task execution performance of aircraft maintenance teams [5]. A team is referred to as "a group of people restricted to having a common goal and typically cooperate and assist each other in achieving their common goal" [6]. People create trust in each other to cooperate in uncertain environments [7]. This research therefore focuses on trust relations between mechanics for their decision-making on the allocation of tasks.

A mathematical model of an aircraft maintenance team using different task allocation methods has been proposed in this research. The modeling technique needed to adhere to three requirements. First, it needed to include the cognitive and social teaming factors in a detailed manner. Moreover, it was required to capture relations between local social aspects and global team performance. The dynamic nature of task allocation also needed to be considered.

Agent-Based Modeling and Simulation (ABMS) was appointed as the most appropriate technique for developing this model. Agent-based methods are applicable for systems with a high level of localization as well as distribution [8]. Besides, they allow for capturing emergent phenomena [9], which can appear when local properties form more complex mechanisms as a collective than as the sum of the individuals [10]. Finally, agent-based models are flexible [9].

The mathematical model has been simulated for a case study on a main landing gear replacement. Three task allocation methods have been modeled: task allocation by a team lead, voting and automated negotiation. Furthermore, the focus was on three types of teams: an independent team, a team compliant with their superior and a socially oriented team. The task execution performance was evaluated for each team type as well as task allocation method. Additionally, the relation between the level of agreement on the task allocation and task execution efficiency was investigated.

Bottom-up modeling methods have not been used for task allocation in aircraft maintenance management research. Usually top-down methods are applied [5]. That is why different research areas were assessed for this study. Next to aircraft maintenance management research, automated negotiation research has been studied for developing task allocation methods. Moreover, the focus on social teaming aspects required a review of Agent-Based Social Simulation research.

This paper has been organized as follows. It starts by providing an overview of the related work in the three research fields in Section 2. After that a description of the case study is provided in Section 3. Section 4 is concerned with the methodology. The theoretical background of teamwork is outlined in Section 5. An informal specification of the proposed agent-based model is presented in Section 6. Section 7 addresses the verification and validation appproach. Section 8 provides the experimental set-up and results. Section 9 discusses the main findings of this research as well reflections on the methodology. Conclusions are drawn in Section 10.

2. Related Work

This multi-disciplinary study contributes to three main research areas: aircraft maintenance management, automated negotiation and agent-based social simulation. The following sections describe related work within these research fields.

2.1. Aircraft Maintenance Management

Research into the process of allocating tasks among mechanics within aircraft maintenance is very limited [11]. More research exists on task scheduling [2] or workforce scheduling [12, 13]. Most studies use top-down approaches for task or workforce scheduling [12–17]. Agent-based modeling techniques have been applied in the aircraft maintenance domain before, both on task [18] or workforce [19] scheduling. Social teaming aspects are not considered in any of these studies. Task scheduling determines when and where maintenance tasks are performed [20]. Workforce scheduling deals with the problem of scheduling mechanics in shifts [12]. Task allocation acts on a lower operational level than task or workforce scheduling. Research into the operational control of aircraft maintenance focuses on the development of Decision Support Systems [11, 21, 22]. None of these studies considers specifically decision-making on task allocation.

2.2. Automated Negotiation

Automated negotiation has been of increasing interest within agent-based modeling [23]. Task allocation is one of the applications for automated negotiation [24]. Previous research presented a cooperative negotiation method for task allocation problems [25]. Game theoretic approaches have been used for task allocation as well [26]. Time constraints have been implemented in an automated task allocation protocol [27]. Others focus on the negotiation on resource allocation [28, 29]. Socially optimal allocations of resources have been aimed for as well [30]. None of these studies have analyzed the behavior of negotiation protocols in varying social environments rather than finding theoretical optimal solutions. Researchers addressed the use of Negotiation Support Systems within real world applications [31]. Attempts for modeling cognitive biases in negotiation have been presented as well [32]. No previous research has applied automated negotiation to task allocation in aircraft maintenance.

2.3. Agent-Based Social Simulation

Social simulation is a relatively new field of research [33]. Yet, a simulation study has been performed on mechanics' motivation for compliance with safety regulations at an aircraft ground service organization [34]. Another research focused on social influences within aircraft maintenance teams on their compliance with safety regulations [35]. Organizations have been studied using social simulation [36]. Social simulation of teamwork dynamics focused on reputation [37], diversity [38], skill [39], trust [40] and power [41] within groups. No integrated model of the social aspects of teamwork has been proposed in research yet. Moreover, researchers have not explored the relation between the sociality of a team and its performance in an applied case study.

The next section will describe the case study that has been modeled in this research.

3. Case Description

A case study has been performed in order to simulate the task execution of an aircraft maintenance team. The requirements for selecting the case were three-fold. First, it needed to facilitate many interactions between mechanics and preferably between different teams. The case sets therefore at a base maintenance environment, where generally large maintenance tasks are performed. Moreover, the tasks needed to have different skill level and safety requirements.

The case therefore comprises the main landing gear replacement of an Airbus A310, which needs to be finished in 48 hours. The tasks are performed by three consecutive teams of five mechanics each. Every shift has a duration of 8 hours. In the beginning of each shift the mechanics join together to discuss the allocation of tasks. Halfway through the shift they can re-allocate tasks. At the end of a shift they communicate the current state of the work with the next team. Performance is evaluated on both time efficiency and ensuring safety.

A specific aircraft maintenance team has been defined in order to simulate the task execution process in detail. This team is an abstraction of an observed team at an aircraft maintenance organization. The team has one mechanic with an EASA C-license, which allows him to sign off all base maintenance tasks. This mechanic is highly skilled and therefore leads the team. Since the team lead has the final responsibility for delivering the aircraft to the airline on time, it prefers time efficiency above safe maintenance work. Three other mechanics have an EASA B1-license, which allows them to perform all tasks of a main landing gear replacement. Their skills are, compared to others, medium level. Most of these mechanics do not have significantly different priorities. Only one mechanic is extremely focused on thorough task execution. Another does not care about efficient task execution at all. The fifth mechanic has no EASA license, but is allowed to work on the main landing gear replacement. Its skill level is low and it does not aim for skillfulness within the team.

Six scenarios have been defined to evaluate the performance of different task allocation methods. In order to make sure that the time needed for simulation was within the time constraints of this research, five scenarios only consider the first shift of the main landing gear replacement. The first scenario comprises a team with relatively independent mechanics, not focused on their fellow team members. The second scenario represents a team motivated by the team lead or management. The third scenario represents an inherently social team. Two variations have been introduced to the social team. In the first variation a new mechanic, which does not know the other mechanics, is introduced to the team. The second variation introduces three new mechanics to the team. The sixth scenario involves the total main landing gear replacement for all six shifts, consisting of socially oriented teams. A detailed overview of these scenarios and the corresponding simulations is presented in Section 8.1.

The next section explains the methodological approach that has been followed for modeling these scenarios.

4. Methodological Approach

Our methodological approach is defined by using a generic agent-based modeling framework, which allows for an all-encompassing specification of an agent-based model [42]. Social simulation approaches, however, require additional methodological considerations to ensure scientific validity. The methodology for the specification of an agent-based model is outlined in Section 4.1 and the approach for agent-based social simulation is explained in Section 4.2.

4.1. Agent-Based Modeling and Simulation

An agent-based model specification consists of three main elements [42]. First, the agents and their local properties should be described. In this study, agents represent the mechanics, and the local properties describe their internal states and actions within the environment. Next, the specification of the environment in which the agents act is provided. The environment contains a description of dynamic processes of all non-agent objects. Furthermore, the interactions between agents and their environment should be specified. Interactions among agents could be induced by communication or coordination mechanisms [43]. Negotiation is a form of coordination and is characterized by agents with conflicting interests still trying to come up to a mutually acceptable agreement [6]. Negotiation requires additional elements to be included in the model specification.

The main ingredients for defining an automated negotiation process are the negotiation set, protocol and strategies [6]. The negotiation set comprises all possible negotiation outcomes. The negotiation protocol describes the rules of interaction for the agents to find an agreement. Common negotiation protocols are alternating-offer protocols, auctions, contract net protocols or voting protocols [23]. Agents' strategies specify the proposals agents make. Agents usually aim at maximizing their utility, which represents their level of satisfaction with a particular outcome [6]. Strategies can be game-theoretic, heuristic or argumentation-based [23].

4.2. Agent-Based Social Simulation

Agent-Based Social Simulation (ABSS) uses agent technology to simulate social phenomena [44]. This research field is still maturing, so no all-encompassing methodology is available [45]. Scientific methodologies, however, require a systematic procedure to reproduce results [46]. Formal languages allow for systematical model descriptions [45].

Social theories can be classified in two categories: normative and descriptive theories. A normative approach to social science aims at representing how people should behave, but the current trend is shifting to descriptive approaches: how people are observed to be behaving. The main criterion for selecting theories from social science in our model is therefore empirical validity: a substantial body of research should confirm the descriptive nature of these theories.

The next section presents the theoretical background on the social theories that have been included in our model.

5. Theoretical Background

This section elaborates on the social theories that represent the social aspects of teamwork in our model. Three characteristics underlie our notion of teamwork.

The first is that teams work together to achieve a common goal [41]. Our work considers the motivation and commitment of agents to specific team-oriented and individual goals. That is why we used an empirically supported theory on human motivation to model people's motivational drivers: Self-Determination Theory. More on this theory can be found in Section 5.1. Moreover, working closely together makes social influences within a team inevitable [47]. Section 5.2 therefore elaborates on social influence research.

The second characteristic of teams is that they collaboratively monitor progress and team efforts [41]. Situation Awareness enables people to evaluate the current state of the environment and is elaborated on in Section 5.3.

The final characteristic is that teams coordinate individual actions for optimal team performance [41]. Our teams coordinate through task allocation. In order to make decisions on task allocation, the mechanics need to predict future states. Reasoning about trust allows for predicting future states in uncertain environments [48]. Section 5.4 therefore describes the theoretical background on trust.

5.1. Self-Determination Theory

Self-Determination Theory considers intrinsic motivation to be driven by internal psychological needs, required for proactivity, development and psychological health [49]. It defines three main needs: the need for competence, the need for relatedness and the need for autonomy. The need for competence is the desire to be competent in one's actions, skills and desires. The need for relatedness reflects the desire to experience a sense of belonging to and interaction with others. The need for autonomy encompasses the desire of being in control of one's own actions.

Later work on Self-Determination Theory identified different types of motivation, called causality orientations [50]. The three causality orientations are the autonomy orientation, in which persons are motivated by their basic needs, the controlled orientation, in people are focused on rewards and the amotivated orientation, driven by anxiety of incompetence.

5.2. Social Influence

Social influence relates to all processes "in which people's attitudes or beliefs are altered or controlled by some form of social communication" [51]. Although many different types of social communication underlie social influence [51], the focus is in this research on compliance and conformity. We refer to compliance as an "agreement to an, explicit or implicit, request" [52]. Conformity captures "a person's change in behavior to adjust to the reactions of others" [52]. This implies that people are externally motivated to comply, while internal motivation for relatedness drives conformity.

People use power to influence others by exercising pressure to stimulate compliance or conformity [53]. We refer to power as "the capacity or ability to change the beliefs, attitudes, or behaviors of others" [53]. Power relations between mechanics have been modeled based on French and Raven's six bases of power [54]. These power bases are the following: legitimate power, based on internalized values of the submissive, referent power, based on relatedness, expert power, based on experience or knowledge, persuasion power, based on information or persuasion, reward power, based on positive incentives and coercive power, based on punishments.

The Social Contagion model by [55] has been adopted to represent social influence dynamics. This model describes how a person adjusts its attitude or belief when meeting another person, based on their difference in attitude or belief and some convergence parameter that reflects the tendency of that person to adopt another's viewpoint. We model this parameter based on social influence and power elements.

5.3. Situation Awareness

Situation Awareness is defined as "the level of awareness a person has of a situation: the dynamic understanding of what is going on" [56]. A widely accepted framework for modeling situation awareness specifies three levels [56]. At the first level a person perceives a state in an environment. The second level is achieved when a person interprets data from level one in relation to its own states and goals. When someone predicts future states of the system based on the current states, the third level of situation awareness is achieved. The prediction of future states in this model is based on trust.

5.4. Trust

Trust can be defined as "a cognitive state in which a person intends to accept vulnerability due to positive expectations of other's intentions or behavior" [57]. Trust can reduce social complexity and allows for decision-making on issues that are otherwise too complex for people [58]. It can be based on direct interactions, such as impressions of another person, or indirect interactions induced by reputation [59]. We model trust in line with the situation awareness framework. Level one situation awareness relates to agents' impressions of other agents. Level two situation awareness is formed when agents construct reputational views of other agents out of these impressions. Level three situation awareness refers to the level of trust that an agent has in another agent.

Trust is self-preserving and self-amplifying [48]. Experimental research, however, showed that negative impressions had a stronger effect on decreasing trust between people than positive impressions increased it [60]. This is in line with Prospect Theory, which assumes that people have a subjective S-shaped value function. Figure 1 shows that this value function is concave for positive and convex for negative experiences, relative to a reference point [61]. Prospect Theory is considered in agents' impressions, reputation and trust.

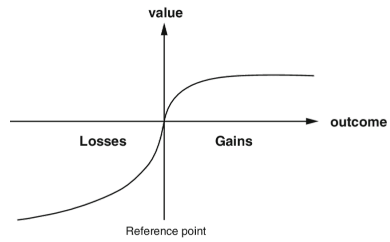


Fig. 1. Subjective value function from Prospect Theory [61]

This concludes the theoretical background. The next section will outline the model design.

6. The Agent-Based Model

Figure 2 shows an overview of the model dynamics. Each arrow represents a causal relation between two components. The next sections will present the model's detailed properties. Section 6.1 outlines the environment specification, followed by the agent specification in Section 6.2. Section 6.3 describes the interaction properties including the task allocation methods. Additional properties for the specification of the interactions between multiple shifts can be found in [62].

6.1. Environment Specification

The environment encompasses the maintenance tasks that are required for a main landing gear replacement. Every shift has the goal of accomplishing a fixed subset of the total amount of tasks. Every task has an associated number of estimated man-hours, number of mechanics required, safety criticality and a number of tasks that are dependent on the completion of this task. Fixed task demands are the skill level required and the thoroughness level required. An agent also creates its own belief about the situational task demands, which depends on its experienced time pressure and the tasks dependency. The task characteristics have been estimated and have been checked by aircraft maintenance technicians.

The tasks assigned to a shift have been grouped into a number of task packages equal to the number of mechanics in a team. The task packages were constructed in collaboration with a certified C-engineer. Negotiation over these packages is also called a package deal procedure and is used in this model for three reasons. First, negotiation over tasks with many dependencies is computationally hard. It has also been

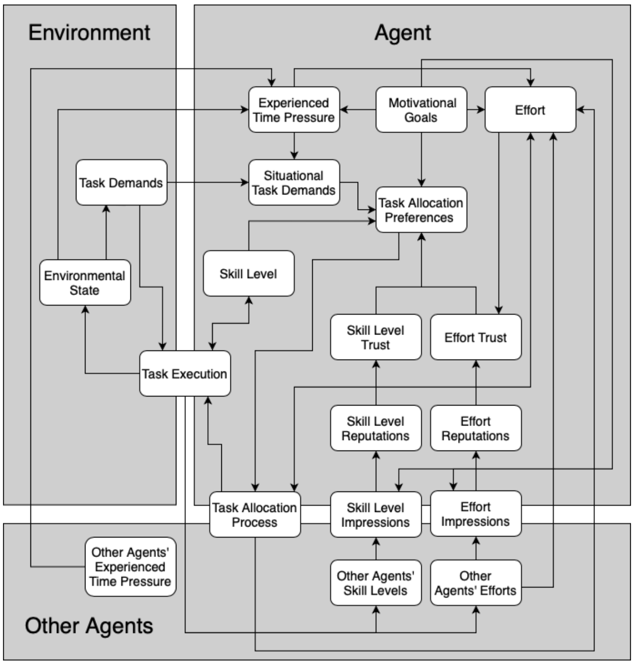


Fig. 2. Overview of the model elements and interactions

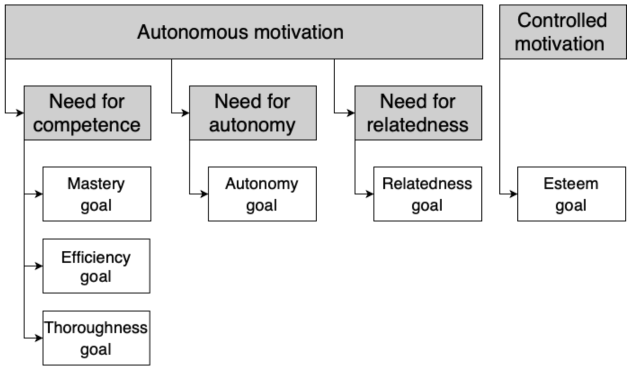


Fig. 3. Agent goals derived from Self-Determination Theory [49]

shown that when the ratio of agents over tasks is small, utilitarian social welfare increases when package deals are used [63]. The utilitarian social welfare is the total sum of all participating agents' utilities for a negotiation outcome. A high utilitarian social welfare indicates a high level of agreement within the team. Furthermore, allocation of task packages rather than individual tasks is more time efficient in real life.

6.2. Agent Specification

The model consists of five aircraft maintenance technician agents, one of which is the team lead (TL) and the other four are mechanics (MECH). The agents have the following characteristics: motivational goals, efforts, skill level and experienced time pressure. Agents' goals will be elaborated on in Section 6.2.1 and the other properties in Section 6.2.2.

6.2.1. Agent Goals

Motivation driving agents' behavior is captured in six different goals. A goal is defined as "an end state to which the agent is striving: the purpose of an activity" [64]. Agent goals are based on the motivation orientations and basic needs in Self-Determination Theory. An overview of these goals can be found in Figure 3. The grey boxes are the theoretical constructs defined in Self-Determination Theory and the white boxes represent the derived agent goals.

Three goals represent the motivational aspects on teamwork: the autonomy goal, relatedness goal and esteem goal. The autonomy goal captures agent's inner drive of being in control of its own decisions. Agents with a high autonomy goal make their decisions based on their own observations. The relatedness goal captures the agent's need for experiencing a sense of belonging with its fellow team members. Agents with a high relatedness goal make their decisions based on beliefs of others. The esteem goal captures the desire of being acknowledged by a superior, such as the team lead or management. Agents with a high esteem goal are externally motivated to comply with a superior's beliefs.

The need for competence is represented by three different goals. The first two goals are associated with the task execution outcome: an agent can aim to execute a task efficiently and thoroughly. From an organizational perspective, time efficiency is the main metric for measuring performance. In safety critical organizations, however, the efficiency-thoroughness trade-off is key [65]. A trade-off has to be made between time and effort on preparing to do something and time and effort on spending doing it. It is therefore not possible to maximize efficiency and thoroughness at the same time [65]. The need for competence also encompasses the mastery goal: the goal of reaching one's inner potential [66]. When tasks and skills are perfectly aligned, people experience a state of flow: intense focus and concentration [67].

All agents have numerical values for these goals. These values represent their motivational drive for achieving a goal and provide an ordering of importance for all goals. A high drive for achieving a goal is represented in the range [0.7-1.0], medium drive [0.4-0.7] and low drive [0.0-0.4].

6.2.2. Agent Efforts, Skill and Experienced Time Pressure

Effort is "the physical or mental activity needed to achieve something" [68]. The agents in this model have two different types of efforts: efficiency effort and thoroughness effort. For model simplicity we assume agents' thoroughness and efficiency effort to be independent. The effort generated by a person is influenced by their motivation [69], task demands [69], maximum capabilities [69] and social influences [35]. In this model, physical factors limiting a person's capabilities, such as fatigue or mental cognitive load are not considered. Rather the agent's effort is initially defined by its motivation, however, influenced over time by task demands, time pressure and social influences from other team members.

Agents have a skill level that reflects their level of mastery of the main landing gear replacement tasks. No differentiation in skill type is made, since most are mechanical tasks.

Moreover, agents have a personal experienced time pressure. This property resembles the agents' stress level. Their experienced time pressure changes over time by monitoring the task execution process and due to social influences.

These characteristics are represented by numerical values in the same ranges as the agent goals. [62] provides a detailed description of the meaning for each variable range.

The next section presents the interaction properties.

6.3. Interaction Specification

The interaction properties are grouped in four categories. Section 6.3.1 presents the interactions between agents during task execution. The interactions between agents for task allocation are outlined in Section 6.3.2. Section 6.3.3 provides the interactions after task allocation. Interactions between agents and the environment can be found in Section 6.3.4.

6.3.1. Interactions between Agents during Task Execution

Interactions between agents occur when they encounter one another during task execution. This happens mostly randomly. If agents are working together on a task, however, they will be influenced by their co-worker. Two types of dynamic properties represent the interactions between agents during task execution: social influence and trust properties.

Social influence - Three cognitive states of agents are influenced by their fellow team members: efficiency effort, thoroughness effort and experienced time pressure. We defined two types of social influence properties: compliance with the team lead and conformity with team members. Five properties represent these social influence dynamics:

1. Efficiency Effort Compliance Property: If a mechanic agent has a belief about its efficiency effort, and it encounters the team lead agent, then at the next time point, it will adjust its efficiency effort according to Equation 1, based on [55].

$$ef^{t+1}_{eff_i} = ef^{t}_{eff_i} + \gamma_{ji} \cdot goal_i(es) \cdot (ef^{t}_{eff_j} - ef^{t}_{eff_i}) \quad \textbf{(1)}$$

t is the time point, ef_{eff_i} is agent i's efficiency effort, ef_{eff_j} is the team lead agent j's efficiency effort, γ_{ji} is the power influence of the team lead agent j on agent i. The social influence between agents is captured in the agent's esteem goal, $goal_i(es)$, which reflects an agent's motivation to comply with the team lead. If for example, team lead j has almost no power over agent i, it is not expected that agent i will adjust to the team lead's efficiency effort. This increases if the agent's high esteem goal motivates him to comply.

2. Efficiency Effort Conformity Property: If a mechanic agent has a belief about its efficiency effort, and it encounters another mechanic agent, rather than the team lead agent, it will adjust its efficiency effort according to Equation 2.

$$ef^{t+1}_{eff_i} = ef^{t}_{eff_i} + \gamma_{ji} \cdot goal_i(re) \cdot (ef^{t}_{eff_j} - ef^{t}_{eff_i}) \quad \textbf{(2)}$$

The agent is now driven by its relatedness goal, $goal_i(re)$, which is its motivation to conform with another agent's effort.

3. Experienced Time Pressure Compliance Property: If a mechanic agent has a belief about its experienced time pressure, etp_i, and it encounters the team lead agent, then at the next time point, it will adjust its experienced time pressure similar as efficiency effort in Equation 1.

4. Experienced Time Pressure Conformity Property: If a mechanic agent has an experienced time pressure, and it encounters a mechanic agent, it will adjust its experienced time pressure similar as efficiency effort in Equation 2.

5. Thoroughness Effort Conformity Property: If an agent has a thoroughness effort, ef_{tho_i}, and it encounters another agent, then at the next time point it will adjust its thoroughness effort similar to efficiency effort in Equation 2. Our case represents a team lead valuing efficiency and ignorant for thoroughness. Since efficiency and thoroughness effort are assumed to be independent, the team lead has no thoroughness effort demands that can be complied with by a mechanic.

Trust - Agents create trust in three aspects of other agents: efficiency effort, thoroughness effort and skill level. These three aspects are represented by the variable ϕ. Six properties represent the creation of impressions, reputation and trust:

1. Impression Property: Agents create perceptions of other agents' efficiency effort, ef_{eff}, thoroughness effort, ef_{tho}, and skill, sk. In line with social comparison theory, agents form perceptions about other agents relative to their own norms [70]. These relative perceptions, $pe_{i\rightarrow j}(\phi)$, are therefore modeled as the observed aspect minus the agent's own internal goal. Equation 3 shows agent i's perception of agent j's efficiency effort, based on its internal goal for efficiency, $goal_i(eff)$. Similarly, an agent creates a relative perception of an agent's skill level in relation to its mastery goal, $goal_i(mas)$, and a perception of an agent's thoroughness effort in relation to its thoroughness goal, $goal_i(tho)$.

$$pe^{t}_{i\rightarrow j}(eff) = ef^{t}_{eff_j} - goal_i(eff) \quad \textbf{(3)}$$

In line with prospect theory, agent i's impression of agent j on aspect ϕ is modeled according to Equation 4 [61]. λ represents an agent's loss aversion factor and α its risk aversion factor. Experimental research has indicated that the values for these variables are 2.25 and 0.88 respectively [71]. If we consider efficiency effort again as an example, the agent's efficiency goal is then its reference point for evaluating other's effort. If an agent's efficiency goal is high, it will perceive a lower efficiency effort as a higher loss for the team than an equally higher efficiency effort as a gain.

$$Imp^{t+1}_{i\rightarrow j}(\phi) = \begin{cases} (pe^{t}_{i\rightarrow j}(\phi))^{\alpha} & \text{if } pe^{t}_{i\rightarrow j}(\phi) \geq 0 \\ -\lambda(-pe^{t}_{i\rightarrow j}(\phi))^{\alpha} & \text{if } pe^{t}_{i\rightarrow j}(\phi) < 0 \end{cases} \quad \textbf{(4)}$$

2. Personal Reputation Property: If agents have had impressions of other agents, they will create reputational views of these agents over time. People generally remember recent impressions better than older ones [72]. We therefore adapted the REGRET model [40], where agent i's reputational view of agent j is modeled according to Equation 5. The equation's first fraction gives more weight to recent impressions.

$$R^{t+1}_{i\rightarrow j}(\phi) = \sum_{Imp^{t_a}_{i\rightarrow j} \in I_{i\rightarrow j}} \frac{\frac{t_a}{t}}{\sum_{b\in I_{ij}} \frac{t_b}{t}} \cdot Imp^{t_a}_{i\rightarrow j}(\phi) \quad \textbf{(5)}$$

3. Social Reputation Property: Research shows that reputation is not only based on individual observations, but also on secondhand information [73]. So when an agent has a reputational view of another agent, it will create a belief about the agent's reputation within the team. Equation 6 shows the creation of the reputation agent j has in the group of agents I. The weights, $w_{i_a I}$, for each agent are calculated as the weighted mean of their abstract power influence within the group, illustrated in Equation 7. γ_{iI} is the power influence of agent i on its entire group I, representing social influences within the team, and is modeled according to Equation 8 [74].

$$R_{I\to j}^{t+1}(\phi) = \sum_{i_a \in I} w_{i_a I} \cdot R_{i_a \to j}^{t}(\phi) \quad \textbf{(6)}$$

$$w_{i_a I} = \frac{\gamma_{i_a I}}{\sum_{i_a \in I} \gamma_{i_a I}} \quad \textbf{(7)} \qquad \gamma_{iI} = \sum_{h \in I, i \neq h} \frac{\gamma_{ih}}{1 + \gamma_{hi}} \quad \textbf{(8)}$$

If an agent has a relatively high power influence on other agents within its group, it is expected that its reputational view will be internalized by other agents faster than for agents with a smaller power influence. In the scenarios with new team members, agents are only influenced by the reputational views of their fellow social group members. Agent i is then influenced by members of social group I. Otherwise, the agent is influenced by the entire team.

4. Personal Group Reputation Property: If new mechanics enter a team, an agent creates a reputational view on both social groups ("old" or "new"). These in-group out-group reputations, $R_{i\to J}^{t+1}(\phi)$, are calculated as in Equation 6: as a weighted mean of the individual reputations for agent j, $R_{i\to j}^{t}(\phi)$. Again using a weighting factor, $w_{j_a i}$, which is, similar as in Equation 7, the weighted mean of the power influences of all agents within group J on agent i, $\gamma_{j_a i}$.

5. Social Group Reputation Property: If an agent has a reputational view of a social group, $R_{i\to J}^{t}(\phi)$, its own group creates a shared view on this other group. This property is updated as in Equations 6, 7 and 8, however for group reputation J, $R_{i_a \to J}^{t}(\phi)$. This results in group reputation $R_{I\to J}^{t+1}(\phi)$, which is an abstract representation of social influences within the groups to decrease computational complexity.

6. Trust Property: If an agent has a belief about the personal and social reputations of an agent, it will create a belief about its trust in agent j on aspect ϕ. If all team members are part of the same social group, they do not have any group reputations and trust is therefore formed according to Equation 9. If there are two social groups within the team, trust is also impacted by their in-group out-group reputations and is updated according to Equation 10. Weights are introduced to represent whether an agent is more inclined towards its own observations, $goal_i(au)$, or others' opinions, $goal_i(re)$. In Equation 10, a factor of $\frac{1}{2}$ is introduced to average the two reputational beliefs for each weighting factor.

$$T_{i\to j}(\phi)^{t+1} = \frac{1 + goal_i(au) \cdot R_{i\to j}^{t}(\phi) + goal_i(re) \cdot R_{I\to j}^{t}(\phi)}{2 \cdot (goal_i(au) + goal_i(re))} \quad \textbf{(9)}$$

We add 1 and divide by 2 for these two equations to model trust between [0,1], rather than as for impressions and reputation on a scale of [-1,1]. This is in line with our definition of trust: the intention to accept vulnerablity for others' behavior. Although negative beliefs for impressions and reputation seem natural, negative intentions for acceptance are rather counter-intuitive. Zero trust indicates no intention to accept vulnerability and trust equal to one means full acceptance.

$$T_{i\to j}(\phi)^{t+1} = \frac{1 + \frac{1}{2} \cdot goal(au)_i \cdot (R_{i\to j}^{t}(\phi) + R_{i\to J}^{t}(\phi))}{2 \cdot (goal(au)_i + goal(re)_i)} + \frac{\frac{1}{2} \cdot goal(re)_i \cdot (R_{I\to j}^{t}(\phi) + R_{I\to J}^{t}(\phi))}{2 \cdot (goal(au)_i + goal(re)_i)} \quad \textbf{(10)}$$

Task allocation based on agents' trust is explained next.

6.3.2. Interactions between Agents for Task Allocation

The interactions between agents for task allocation are modeled using the three negotiation elements: negotiation sets, protocols and strategies. The negotiation set is represented as all possible allocation options. It is therefore necessary for agents to create a belief on their value for a specific allocation option. An overview of the properties representing the agents' valuation of options is therefore provided first. The three task allocation protocols and strategies are explained afterwards, starting with team lead decision-making, followed by voting and mediated feedback automated negotiation.

Valuation - The negotiation set is represented by the set of all possible allocation outcomes. Each agent determines its value for the assignment of task packages among all agents. An agent's valuation is calculated using three properties:

1. Task Demands Property: If an agent has a belief about its experienced time pressure, and tasks need to be distributed within the team, then at the next time point it will create a belief about the demands, $dem(\phi)_{i,f}^{t}$, for every task. The thoroughness and skill demands are equal to task f's required thoroughness level, tho_f^{req}, and task f's required skill level, sk_f^{req}. The level of efficiency required, however, does not depend only on the task, but also on the current state of the task execution. If an agent's experienced time pressure is low, the efficiency demand will be low for every task. If the agent's experienced time pressure is high, the task with the largest number of tasks dependent on its completion can be viewed as the most urgent task. The efficiency demand is therefore modeled as a multiplication of an agent's experienced time pressure and the normalized number of tasks dependent on the completion of task f within this shift, dep_f. The efficiency demand of task f is then calculated as follows: $dem(eff)_{i,f}^{t} = dep_f \cdot etp_i^{t}$.

2. Trust in Tasks Property: If an agent has a belief about the demands for every task, it will create a belief about its trust in the competence of agent j executing tasks f within the task package p. Agents aim to minimize under-competence, such that the task demands are satisfied as much as possible. This is calculated according to Equation 11, based on [75].

$$T_{i\to j}(\phi(p))^t = \sum_{f\in p} 1 - max\left(0, \frac{dem(\phi)^t_{i,f} - T_{i\to j}(\phi)^t}{dem(\phi)^t_{i,f}}\right) \quad \textbf{(11)}$$

So, if the efficiency demand for task f is equal to or lower than agent i's trust in agent j's efficiency effort, then agent i's trust in agent j efficiently executing task f is equal to 1. If agent i has half the trust in agent j's efficiency effort than the efficiency demand, its trust in agent j efficiently executing task f is also 0.5. For each task package, the agent sums its trust in the execution of all tasks for each aspect ϕ.

3. Valuation Property: Agent i's valuation, $V_i(o)$, for an allocation option, o, of all agents j in team q assigned to packages p_j is then calculated according to Equation 12. We model this for the total allocation of task packages within the team, since the value of assigning package 1 to agent A, depends on which package is then assigned to agent B etc.

$$V_i^{t+1}(o) = \sum_{j\in q}\Bigg(\frac{goal_i(mas)\cdot T_{i\to j}(sk(p_j))^t}{goal_i(mas)+goal_i(eff)+goal_i(tho)} + \frac{goal_i(eff)\cdot T^t_{i\to j}(eff(p_j))^t}{goal_i(mas)+goal_i(eff)+goal_i(tho)} + \frac{goal_i(tho)\cdot T^t_{i\to j}(tho(p_j))^t}{goal_i(mas)+goal_i(eff)+goal_i(tho)}\Bigg) \quad \textbf{(12)}$$

Agent i believes that the option with the highest valuation presents the best fit between mechanics and tasks. We model this as an additive utility function, since the three aspects of mechanics' work are independent variables. Agent i's internal goals define whether it gives more weight to efficient task execution, $goal_i(eff)$, thorough task execution, $goal_i(tho)$, or the alignment of tasks and skills, $goal_i(mas)$.

The task allocation procedures will be described next.

Team Lead Decision-Making - The introduced technologies at the maintenance organization under consideration required the team lead to allocate tasks. The team lead chooses the allocation option it values the most. This is formally represented in Equation 13, where $o*$ is the chosen allocation.

$$o*^{t+1} = argmax_o \; V_i(o)^t \quad \textbf{(13)}$$

Voting Protocol and Strategies - A voting protocol is explored, because the mechanics at the maintenance organization used self-built voting protocols for scheduling. The voting protocol can be found in Figure 4 (a). First, all team members evaluate the optional allocations according to Equation 12 and communicate two of their most preferred options to an auctioneer. The auctioneer communicates the proposed options to all agents, which will then pose a bid for every option. The auctioneer uses the Clarke tax algorithm to calculate the winning option according to Equation 14 [76]. The Clarke tax is a mechanism that motivates agents to reveal their preferences truthfully, therefore preventing strategic voting [76].

$$o*^{t+1} = argmax_o \sum_i V_i(o)^t \quad \textbf{(14)}$$

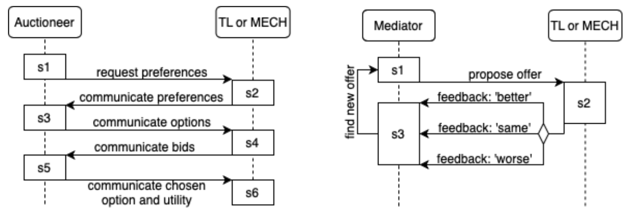
The introduction of a Clarke tax has truthful bidding as a dominant strategy [77]. It is however not resistant to collusion [77]. We introduce an additional tax to discourage collusion between two agents belonging to the same group. Agents are not expected to collude if their combined utility will not increase, since power influences within groups are assumed to be similar. Agents' utilities are calculated according to Equation 15, where tax_i is the Clarke tax and tax_{Ii} the group tax, calculated by Equations 16 and 17 respectively.

$$u_i(o*)^{t+1} = V_i(o*)^t - tax_i^t - tax_{Ii}^t \quad \textbf{(15)}$$

$$tax_i = \sum_{j\neq i} V_j(argmax_o \sum_{k\neq i} V_k(o)) - \sum_{j\neq i} V_j(o*) \quad \textbf{(16)}$$

$$tax_{Ii} = \sum_{j\neq i} V_j(argmax_o \sum_{k\neq i} V_k(o)) - \sum_{h\neq G} V_h(o*) \quad \textbf{(17)}$$

Mediated Feedback Based Protocol and Strategies - An automated negotiation protocol could increase the performance of the decision-making process. The Mediated Feedback Based Protocol allows agents to provide feedback to a mediator on proposals. This protocol was selected, because it represents the team dynamics of exchanging arguments and has shown to produce good results under time constraints [78].



(a) Voting protocol (b) Mediated feedback protocol

Fig. 4. Agent's states and interactions for both negotiation protocols

Figure 4 (b) provides an overview of the Mediated Feedback Based Protocol. The mediator generates a first bid randomly and sends it to all agents. Each agent evaluates the offer and compares this offer to the previous offer. The agent communicates to the mediator if this new offer is 'better', 'worse' or the 'same' as the previous offer. The mediator keeps updating its offer, using preference profiles deducted from the received feedback, until the negotiation deadline. The winning option is then the last offer that did not receive a 'worse' feedback. For a more detailed explanation refer to [78]. We adopt the hill-climber agent strategy from [78], since it produced a good agreement in a short time.

6.3.3. Interactions between Agents after Task Allocation

After task allocation has been performed, mechanics can estimate their reputation within the team based on the task package that has been assigned to them. This cognitive process is often referred to as theory of mind.

Theory of mind - Theory of mind is "an agent's ability to reason about the beliefs of others" [79]. The agents aim for a reputation in line with their own efforts. If their believed reputation is lower than their effort, they will increase their effort in order to increase their reputation. Three properties represent agents' theory of mind capabilities:

1. Trust Impression Property: An agent will create a belief about the team's trust in its efficiency and thoroughness effort based on the chosen allocation. We only consider effort since agents cannot instantly change their skills. For efficiency effort for example, this is modeled using Equation 18, where $Imp_{i \to q}^{t+1}(T_{q \to i}(eff))$ is the impression that agent i has of team q's trust in agent i on its efficiency effort. Team q has assigned task package p_i to agent i.

$$Imp_{i \to q}^{t+1}(T_{q \to i}^{t}(eff)) = \frac{goal(eff) \cdot T_{i \to i}(eff(p_i))}{F_p} \tag{18}$$

$T_{i \to i}(\phi(p_i))$ is agent i's own trust in carrying out its assigned task package efficiently, and is again calculated according to Equation 11. In order to evaluate all task packages on the same scale, we divide by the number of tasks within package p, F_p. This results in the average trust for all tasks within a package, which is multiplied with the agent's efficiency goal to accommodate for the fact that efficiency could be unimportant to agent i. Thoroughness effort has been modeled in a similar manner.

2. Reputation in Team Property: If an agent has formed an impression on the team's trust in its effort, it will create a belief about its reputation within the team, $R_{q \to i}^{t}(T_{i \to q}(\phi))$. This is again calculated according to Equation 5.

3. Reputation Effort Change Property: If an agent has a belief about its reputation, it will adjust its efficiency and thoroughness effort, based on the gap between their believed reputation and their real effort, according to Equation 19.

$$ef_{eff_i}^{t+1} = ef_{eff_i}^{t} - \omega_q \cdot (R_{q \to i}(T_{i \to q}^{t}(eff)) - ef_{eff_i}^{t}) \tag{19}$$

ω_q determines how motivated the agent is to adjust its effort and is calculated according to Equation 20. γ_{qi} is the power influence of team q on agent i and $goal_i(re)$ agent i's internal drive for relatedness with its peers.

It depends, however, whether the agent's believed reputation is higher or lower than its effort. Remember that the agents aim to have a reputation in line with their efforts or higher. If an agent's efficiency effort is higher than its believed reputation, the agent will increase its effort in order to increase its reputation. A high relatedness goal and team influence will motivate the agent to have this desired reputation within the team. If an agent's efficiency effort is lower than its believed reputation, the agent could decrease its effort, since it already has its desired reputation. But if the agent has a high relatedness goal and team influence, the agent would still aim for maintaining its efficiency effort close to its believed reputation rather than decreasing it.

$$\omega_q^t = \begin{cases} \gamma_{qi} \cdot goal_i(re) & \text{if } ef_{eff_i}^{t} \geq R_{i \to i}(T_{q \to i}^{t}(eff)) \\ (1-\gamma_{qi})(1-goal_i(re)) & \text{else} \end{cases} \tag{20}$$

The abstract representation of the entire team's power influence on the agent is modeled using the Dynamic Theory of Social Impact [80]. N is the number of agents within the team and it is assumed that the agents interact with each other without intermediate agents and therefore their closeness parameter $cl_{ki} = 1$. β is a constant that compensates for group size and experimental research found it to be around 0.5 [81].

$$\gamma_{qi} = N^{\beta}[\sum_{k=1 \ldots N} (\gamma_{ki}/cl_{ki}^2)/N] \tag{21}$$

Agents also have theory of mind capabilities for team lead decision-making. In all of the previous properties, q should then be replaced with the team lead j. Moreover, the agent's relatedness goal, $goal_i(re)$, should be replaced with the agent's esteem goal, $goal_i(es)$, in Equation 20. The team lead has no theory of mind properties for team lead decision-making.

Interactions between agents and tasks are presented next.

6.3.4. Interactions between Agents and the Environment

Two types of properties represent interactions between agents and tasks: task execution and tracking progress.

Task Execution - All agents will start executing tasks after task allocation has been performed. The following four properties represent the task execution dynamics:

1. Start Task Property: If the chosen task allocation has been communicated to the agent, it will start with the execution of the first task of its assigned package.

2. Task Execution Property: If an agent has started executing a task, it will continue executing this task until the task is finished. The task execution time is impacted by an agent's efficiency effort, thoroughness effort and skill level. These temporal relations are calculated relative to the number of man-hours for each task and have been verified with maintenance engineers. A low efficiency effort on a large task therefore results in more additional execution time than for a small task. Assuming that multiple mechanics working on the same task perform the same share, the number of man-hours is divided by the number of mechanics.

We model the task execution dynamics as $p_{i,f}^{t}$, representing the part of a task f that has been finished by agent i at time t. This part is updated every time step according to Equation 22, where $mech_f$ is the number of mechanics for a task, h the time step in hours and mh_f the number of man-hours for a task. The additional part of a task that has been performed in a time step is the length of the time step divided by the total number of man-hours per mechanic. $efi_{f,i}$, $ski_{f,i}$ and $thi_{f,i}$ are influences of efficiency, skill and thoroughness on execution time. These three factors are elaborated on further.

$$p_{f,i}^{t+1} = p_{f,i}^{t} + \frac{h \cdot mech_f}{mh_f} \cdot (efi_{f,i}^{t} + ski_{f,i}^{t}) - thi_{f,i}^{t} \tag{22}$$

Obviously, high efficiency effort results in less execution time. In our model it is assumed that if an agent has average efficiency effort, $ef_{eff} = 0.5$, it will take as much time as the number of man-hours for task f. Extremely low efficiency effort, equal to 0, is assumed to increase execution time with half the task's man-hours per mechanic. High efficiency effort leads to only half of the task's man-hours per mechanic. The efficiency influence, efi, on the part that has been performed in a time step is calculated according to Equation 23.

$$efi_{f,i}^{t} = \frac{1}{1.5 - ef_{eff_i}^{t}} \tag{23}$$

If a mechanic has lower skills than required for a task, it takes more time for this agent to get to know the task, read documentation and understand what is expected. That is why additional time is calculated as the relative difference between the required skill level, sk_f^{req} and the agent's skill level sk_i^t multiplied with the amount of man-hours for a task. This is calculated according to Equation 24.

$$ski_{f,i}^t = max(sk_f^{req} - sk_i^t, 0) \tag{24}$$

If an agent's thoroughness effort is equal or higher than the required thoroughness level, the agent is expected to be as thorough as necessary. A lack of thoroughness effort for a specific task, however, can lead to a safety incident. To model this, we draw a uniformly distributed variable, σ_f, between [0,1]. If this variable is smaller than half the difference in thoroughness effort and thoroughness required, a safety incident occurs. This is modeled according to Equation 25.

$$thi_{f,i}^t = \begin{cases} sc_f & \text{if } \sigma_f < \frac{1}{2}(tho_f^{req} - ef_{tho_i}^t) \\ 0 & \text{else} \end{cases} \tag{25}$$

For example, if the required thoroughness is 1 and an agent's thoroughness effort is 0, the expected value of a safety incident is 1 in 20 minutes of task execution. 0.1 thoroughness difference results in an expected value 1 safety incident in 200 minutes of task execution. No main landing gear replacement task takes such a long time for one mechanic. Thus, a safety incident is much less likely to occur. But if a safety incident occurs, the agent needs to re-do certain parts of the task. The part, $p_{f,i}^t$, is then decreased with the tasks' safety criticality, sc_f. It is assumed that a safety incident can only happen once per task.

3. Start New Task Property: If $p_{f,i}^t \geq 1$, the agent has finished task f. The agent will check whether all the required tasks for starting its next task, task $f+1$, have been finished and afterwards start executing task $f+1$.

4. Skill Dynamics Property: At each time point, if an agent is executing a task with a higher skill level required than its own skill, its skill level increases according to Equation 26. It is expected that mechanics with a high mastery goal will be more open for learning from new experiences, which is why the agent's mastery goal, $goal_i(mas)$, is included. Agents are not assumed to lose skills over time.

$$sk_i^{t+1} = sk_i^t + goal_i(mas) \cdot ski_{f,i}^t \tag{26}$$

Tracking Progress - The team lead agent tracks the team's progress during the shift. The following three properties are defined for the team lead to track progress:

1. Track Packages Property: At each time point, if any of the agents has finished a task, the team lead will update its belief about the to be executed task packages for each agent.

2. Experienced Time Pressure Change Property: At each time point, if the team lead has a belief about the to be executed task packages, it creates a belief about its experienced time pressure according to Equation 27. etp is the experienced time pressure, mhr^t the ratio of the total man-hours left over the shift's total scheduled man-hours and $timer^t$ the ratio of the remaining time over the total shift time.

$$etp_i^t = \begin{cases} 1.5 - min(1.5, \frac{timer^t}{mhr^t}) & \text{if } \frac{timer^t}{mhr^t} < 1 \\ 1.5 - max(0.5, \frac{timer^t}{mhr^t}) & \text{else} \end{cases} \tag{27}$$

For example, four equally large tasks need to be finished in four hours. At the start, the share of man-hours to be performed is equal to the share of remaining time. The team lead's experienced time pressure is then 0.5. If two tasks still need be performed in three hours, the team lead's experienced time pressure will drop to 0, since they have 1.5 times the expected task execution time to finish. In contrast, if two tasks need to be performed in one hour, the team lead's experienced time pressure will be equal to 1, since the team has now only half of the estimated time to finish these tasks.

3. Efficiency Effort Property: If the team lead has an experienced time pressure, it will change its efficiency effort according to Equation 28. If the team lead's experienced time pressure is higher than the average time pressure of 0.5, it will increase its efficiency effort. If it is lower the team lead will decrease its efficiency effort. The magnitude depends on the team lead's esteem goal, $goal(es)$, which motivates him to comply with its manager's requirements.

$$ef_{eff_i}^{t+1} = ef_{eff_i}^t + goal(es) \cdot (etp_i^t - 0.5) \tag{28}$$

This concludes the model description. The next section elaborates on the verification and validation approach.

7. Verification and Validation

Model verification has been performed by testing the underlying model assumptions with experts and face validity of the conceptual models [82]. The implementation has been verified by unit testing as well as solving compile errors. Face validity of the implemented model provided insights in whether the conceptual model resulted in the expected model behavior, which was derived from the underlying model assumptions and social theories. Every iteration several properties were added to the model and the resulting model behavior was evaluated for different inputs. Sensitivity analysis has been performed for the final model. Both the sensitivity analysis and an overview of the model assumptions are provided in [62]. Moreover, we compared our results with other research on group decision-making for further validation.

The results and experimental set-up are presented next.

8. Experiments

This section presents the experiments. Section 8.1 elaborates on the scenarios as well as the simulations that have been performed. The performance indicators for assessing these simulations are described in Section 8.2. An explanation of the statistical evaluation of the results is provided in Section 8.3. The results are presented in Section 8.4.

8.1. Scenarios and Simulation Set-up

The characteristics of the aircraft maintenance team, specified for our described case, can be found in Table 1. The initial states were drawn from a uniform distribution in three ranges: low [0.1-0.4], medium [0.4-0.7] or high [0.7-1.0].

Table 1. Fixed agent characteristics for all simulations

Agent	*sk*	*goal(eff)*	*goal(tho)*	*goal(mas)*
TL-1	High	High	Low	High
MECH-2	Medium	Medium	High	Medium
MECH-3	Medium	Low	Medium	Medium
MECH-4	Medium	Medium	Medium	Medium
MECH-5	Low	Medium	Medium	Low

The following sections will elaborate on the defined scenarios as well as the simulations that have been performed for each scenario, including initial parameters and states.

8.1.1. *Main Scenarios and Simulations*

Three main scenarios have been modeled: an independent (SC-IND), compliant (SC-COM) and social (SC-SOC) team.

SC-IND - The first scenario represents a team of independent mechanics that have been working together for a long time. They share common goals for efficient and safe task execution, but have different beliefs on how to reach those goals. The mechanics value autonomous decision-making and their behavior is relatively independent of their fellow teammates.

SC-COM - In the second scenario the mechanics have known each other for a long time as well, but value compliance with a superior instead of independence. They are driven by external rewards for adhering to their superior's goals. They are not completely driven by their superior, however, and still have individual goals as well.

SC-SOC - The third scenario represents an inherently social team, with mechanics mostly valuing their peer's opinions. They know each other well and therefore have beliefs about other's competence and created social norms on work effort.

The first shift of a main landing gear replacement is simulated for all three task allocation methods in each scenario. The performed simulations and initial states can be found in Table 2. In every simulation either the mechanics' autonomy goal, esteem goal or relatedness goal is high. All agents are part of the same social group in these scenarios. Power relations between mechanics that know each other well are based on high referent and legitimate power, which is derived by [35] to be $\gamma_{ji} \sim U$[0.8,0.9]. The team lead's additional punishment and reward power will not increase this value, since using its formal power would decrease its legitimate and referent power. The simulations have been initialized for three shifts to represent the mechanics' long working relationship.

8.1.2. *Scenario Variations and Simulations*

Three additional scenarios have been introduced to evaluate variations to the model: the introduction of a new team member (SC-NEW-1), three new team members (SC-NEW-3) and task execution by multiple shifts (SC-SHIFTS).

Table 2. Overview of all simulations

Simulation	*goal(au)*	*goal(es)*	*goal(re)*	Allocation protocol
SC-IND-TL	High	Low	Low	Team lead
SC-IND-VO	High	Low	Low	Voting
SC-IND-MF	High	Low	Low	Mediated feedback
SC-COM-TL	Low	High	Low	Team lead
SC-COM-VO	Low	High	Low	Voting
SC-COM-MF	Low	High	Low	Mediated feedback
SC-SOC-TL	Low	Low	High	Team lead
SC-SOC-VO	Low	Low	High	Voting
SC-SOC-MF	Low	Low	High	Mediated feedback
SC-NEW-1	Low	Low	High	Voting
SC-NEW-3	Low	Low	High	Voting
SC-SHIFTS	Low	Low	High	Voting

SC-NEW-1 - It is common in aircraft maintenance to hire temporary workers to fill in the gaps of a workforce shortage [3]. The first variation therefore evaluates what happens when a new mechanic will join the socially oriented team.

SC-NEW-3 - The second variation introduces three new team members to a social team, one of which is the team lead. This is in line with current social dynamics at aircraft maintenance organizations, of which many are dealing with an aging workforce [83]. The transition phase can create an in-group out-group environment within the team [84].

SC-SHIFTS - The final variation considers the entire main landing gear replacement, with six consecutive shifts. This scenario can evaluate whether social influences between mechanics of different shifts impact the task allocation outcome.

These scenarios could only be simulated for one task allocation method due to time constraints. We chose the voting protocol since it was one of the self-built democratic planning systems at the aircraft maintenance organization. The initial parameters for these simulations are also provided in Table 2. SC-NEW-1 and SC-NEW-3 have been simulated for the first shift, while SC-SHIFTS considers the total main landing gear replacement. The older mechanics have been initialized for three shifts again. The new mechanics entered the simulation after two shifts to create at least some initial trust beliefs.

The power relations between old (o) and new (n) mechanics have again been derived form [35]. The older mechanics have not only referent and legitimate power over the new mechanics, but also expert power: they know the organizational norms and their peers better: $\gamma_{on} \sim U$[0.8,1.0]. New mechanics have only persuasion power over older mechanics and due to their lack of knowledge, this is very low: $\gamma_{no} \sim U$[0.0,0.1]. High referent power is present between new mechanics: $\gamma_{nn} \sim U$[0.1,0.4] and as before: $\gamma_{oo} \sim U$[0.8,0.9]. The time step was 10 minutes for all 12 simulations.

8.2. Performance Indicators

Six performance indicators have been defined to evaluate and compare the simulations. The first is the total task execution time in minutes (TIM), which ultimately provides insights into the overall time efficiency performance. The number of safety incidents (SAF) illustrates the safety performance. The absolute task execution time in minutes (TAS) is the sum of the absolute execution time for all tasks within a shift. This measure is relevant since it provides an indication of the efficiency of all team members' task execution efforts. The Utilitarian Social Welfare (USW) is the sum of all agents' utilities for a task allocation outcome averaged over the number of task allocations within a shift. This measure reflects the level of agreement within a team on an allocation outcome. An agent's utility is calculated as its valuation for an option divided by its maximum valuation for all options. In order to be able to compare all scenarios, the Clarke tax has not been considered in the calculation of USW for the voting protocol. The average percentile deviation of man-hours, Δ MH, represents the average of the relative change in execution time for all tasks. This shows how well the average mechanic-task fit is within a simulation. The allocation outcome (ALL) checks whether the allocations within a shift are the same (1) or different (0). This measure provides insights into the task allocation protocol's behavior over time.

8.3. Statistical Evaluation

The Kolmogorov-Smirnov test showed that the simulation outcomes were not normally distributed. The number of simulations was therefore determined by evaluating the coefficient of variation on all performance indicators [85]. It was observed that after 200 runs the coefficient of variation for all single shift simulations remained stable. SC-SHIFTS was already stable after 45 runs. Statistical significance has been calculated for all performance indicators using the Vargha-Delaney A-test [86], except for the task allocation check (ALL). The A-test values express the probability that the performance indicator is higher for the first than for the second algorithm. ALL is evaluated using the Fisher test [87].

8.4. Results

The results of the first scenario with relatively independent mechanics (SC-IND) are provided in Section 8.4.1. After that a description of the results for the scenario with mechanics that value compliance (SC-COM) is provided in Section 8.4.2. The scenario with social mechanics (SC-SOC) is discussed in Section 8.4.3. The results of the social scenario variations are described in Section 8.4.4. A comparison across scenarios is performed in Section 8.4.5 and a more detailed evaluation of the relation between the performance indicators and the social welfare can be found in Section 8.4.6.

8.4.1. SC-IND: Results

The summary statistics for the scenario with independent mechanics are presented in Table 3. Table 4 shows the test statistics for both negotiation protocols compared to task allocation by the team lead. These results are discussed next.

The total task execution time mean is lowest for decision-making by the team lead, followed by the mediated feedback protocol. This can be explained by the fact that in this scenario agents make decisions relatively independent of others and the team lead has a high efficiency goal. The absolute time for all tasks is therefore also lowest for the team lead. The number of safety incidents, however, is significantly higher for the team lead than for the voting or mediated feedback protocol. Only allocating for efficiency therefore results in more safety incidents.

Table 3. SC-IND: summary statistics

		TIM [min]	SAF [-]	TAS [min]	USW [-]	Δ MH [-]	ALL [-]
Team lead	μ	434.4	7.340	1505	4.969	0.250	0.000
	σ	12.94	2.034	34.63	0.010	0.027	0.000
Voting	μ	500.8	5.560	1547	4.986	0.099	0.175
	σ	15.50	1.820	26.63	0.001	0.016	0.391
Mediated feedback	μ	470.5	5.520	1514	4.974	0.248	0.075
	σ	68.99	2.030	61.04	0.008	0.058	0.264

Table 4. SC-IND: test statistics

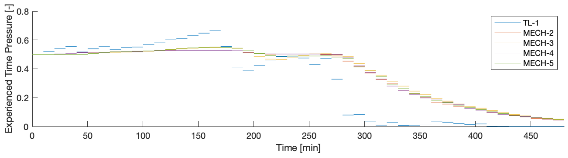
	TIM (A-Test)	SAF (A-Test)	TAS (A-Test)	USW (A-Test)	Δ MH (A-Test)	ALL (Fisher)
Voting	0.00	0.74	0.21	0.00	1.00	1.00
Mediated feedback	0.38	0.47	0.73	0.41	0.55	1.00

The standard deviation for both the total execution time and the absolute execution time of the mediated feedback protocol is relatively high compared to the other two protocols. An explanation is that the mediator could not yet create accurate preference profiles of the agents. This could result in local optima, dependent on the mediator's initial proposal. The standard deviation of the number of safety incidents, however, is not significantly higher than for the other two methods. A possible explanation for this might be that there is a maximum thoroughness violation that can be accepted by one or more agents, regardless of the offer sequence.

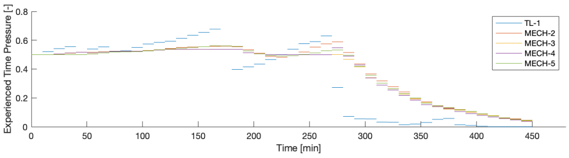
The voting protocol's mean social welfare is the highest of all task allocation methods. This was expected, because the voting protocol selects the outcome with the highest social welfare. The social welfare mean for the team lead and mediated feedback protocol are in the same range with a larger standard deviation. The A-test results in Table 4 show a probability of 0.41 that the team lead provides a better social welfare than the mediated feedback protocol. The mediated feedback protocol has therefore a significant probability of achieving a better social welfare than the team lead.

The voting protocol has a significantly lower average percentile deviation to the number of man-hours than the other two protocols. The additional time for the voting protocol is therefore caused by large tasks. A small percentage deviation still results in a lot of absolute additional time. The team lead and mediated feedback protocol have on average higher deviations, but on shorter tasks, resulting in less lost time.

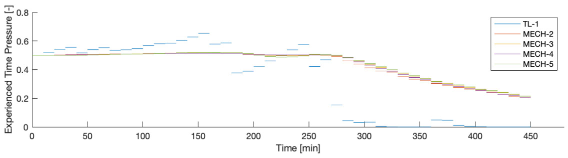
The team lead's allocation check of 0 means that it always changes the allocation half-way through the shift. This can be explained by its changing experienced time pressure over time. The other agents are less susceptible to time pressure due to their autonomous decision-making, which results in the same negotiation outcome more often for the voting and mediated feedback protocols. This difference in experienced time pressure for the team lead and other agents can be seen in Figure 5 (a). Another interesting observation is that the experienced time pressure has an oscillatory shape. This shows that an increase in time pressure leads to increased efficiency effort of the mechanics, which results in a decrease in time pressure and therefore decreasing efficiency effort.



(a) SC-IND



(b) SC-COM



(c) SC-SOC

Fig. 5. Experienced time pressure for team lead allocation

8.4.2. SC-COM: Results

Table 5 provides an overview of the summary statistics for the scenario with compliant mechanics. The test statistics, compared to team lead allocation, can be found in Table 6.

The total execution time is again smallest for the team lead, but this time followed by the voting protocol. The team lead and voting protocol show statistically significant better results for total execution time as well as safety incidents compared to the previous scenario. In the current scenario, agents are driven by their esteem goal, therefore susceptible to the team lead's high efficiency goal. The team lead also has an increased experienced time pressure due to its high esteem goal. It is therefore counter-intuitive that the mediated feedback protocol has a higher total execution time than before. The A-test value, however, indicates that this probability is 0.51: there is no significant difference.

The decrease in the number of safety incidents for all protocols with respect to the previous scenario is striking. For the team lead this could partly be explained by the agents' theory of mind capabilities. An explanation for the other simulations is a decrease in absolute execution time due to the higher efficiency effort of agents. Less execution time decreases the probability of a safety incident in our model, since safety incidents can occur randomly at every time point.

The team lead and voting protocol both have a decrease in social welfare with respect to the previous scenario, which indicates more divergent preference profiles among agents. Further analysis showed a significant difference between the social welfare of the first and second task allocation. This is a result of the larger variations in experienced time pressure at the time of re-allocation (t=240), which can be observed for the first two scenarios in Figure 5. The maximum social welfare is therefore lower during re-allocation. Similar patterns were observed for voting and mediated feedback.

Table 5. SC-COM: summary statistics

		TIM [min]	SAF [-]	TAS [min]	USW [-]	Δ MH [-]	ALL [-]
Team lead	μ	415.5	5.025	1502	4.948	0.213	0.000
	σ	11.68	1.786	37.67	0.007	0.039	0.000
Voting	μ	439.7	4.575	1520	4.974	0.210	0.340
	σ	13.96	1.688	35.23	0.003	0.034	0.475
Mediated feedback	μ	481.8	4.590	1490	4.974	0.217	0.210
	σ	81.79	1.833	69.55	0.006	0.060	0.405

Table 6. SC-COM: test statistics

	TIM (A-Test)	SAF (A-Test)	TAS (A-Test)	USW (A-Test)	Δ MH (A-Test)	ALL (Fisher)
Voting	0.10	0.57	0.37	0.00	0.52	1.00
Mediated feedback	0.22	0.57	0.53	0.01	0.46	1.00

The voting and mediated feedback protocol provide more often the same outcome during re-allocation than in the previous scenario. This is somewhat surprising since the agents have internalized the experienced time pressure more. This influence is less evident than for the team lead since the other agents do not have a high efficiency goal. Part of the explanation can be found in the agents' trust in others. It was observed that the minimum and maximum trust values of all mechanics were less extreme than in the previous scenario. In this scenario the agents are more prone to the opinions of others for establishing trust relations, which creates more shared trust beliefs. Shared trust values lead to more agreement on the allocation outcome. Small differences in trust over time have therefore less impact on the final outcome. Figures of agents' trust over time for each scenario can be found in [62].

Table 6 shows that the differences between the team lead allocation and other protocols are less significant than in the previous scenario. This shows that when all agents are strongly motivated by their superiors, the decision-making protocol is of less importance than for independent teams. One could argue that to a certain degree a norm has been established on how to allocate the tasks within the team.

8.4.3. SC-SOC: Results

Table 7 presents the summary statistics for the scenario with social mechanics. The team lead has significantly better results for total execution time and safety incidents compared to the independent scenario, but not compared to the compliant scenario. The absolute task execution time has decreased with respect to both scenarios. This can partly be explained by the social influences between team members: norms on thoroughness effort are created. The agents' efforts have converged faster during initialization than in the previous scenarios, which increases the team lead's thoroughness effort, resulting in less safety incidents and absolute execution time.

The voting protocol has statistically significant better results for both time performance indicators as well as safety incidents compared to the previous scenarios. The mean absolute execution time and the number of safety incidents of the voting protocol is lowest for all methods and scenarios. The variance of the task execution time is highest, which can illustrate the uncertainty of how norms develop over time.

The mediated feedback protocol has a significantly increased task execution time, but there is no statistical sig-

Table 7. SC-SOC: summary statistics

		TIM [min]	SAF [-]	TAS [min]	USW [-]	Δ MH [-]	ALL [-]
Team lead	μ	417.6	4.580	1474	4.985	0.208	0.000
	σ	11.96	1.564	34.63	0.007	0.022	0.000
Voting	μ	431.6	3.660	1437	4.995	0.139	0.000
	σ	30.56	1.688	33.69	0.001	0.026	0.000
Mediated feedback	μ	533.0	5.140	1488	4.981	0.203	0.140
	σ	56.23	2.472	96.85	0.008	0.099	0.348

Table 8. SC-SOC: test statistics

	TIM (A-Test)	SAF (A-Test)	TAS (A-Test)	USW (A-Test)	Δ MH (A-Test)	ALL (Fisher)
Voting	0.34	0.569	0.80	0.00	0.97	0.00
Mediated feedback	0.02	0.45	0.55	0.91	0.65	1.00

nificant difference with respect to the safety incidents. The absolute execution time, however, is not significantly higher than for the other scenarios. This shows that the increase in total execution time is mostly caused by coordination.

Social relations between agents have created decision-making norms, which can be derived from the highest social welfare for all decision-making methods compared to other scenarios. This can be explained by the creation of trust norms. As mentioned in Section 8.4.2, a relative increase of agents' relatedness goals compared to autonomy goals, results in more influences within the team on their trust beliefs. This creates more coherent preferences profiles across the team, resulting in a higher utilitarian social welfare.

The deviation of man-hours for the voting protocol is, as explained in Section 8.4.1, significantly lower than for the other methods. The voting protocol's absolute execution time is also lower than for the other methods. This shows that the mechanic-task fit is on average highest for the voting protocol, since all temporal relations for task execution are based upon the task's relative duration in this model.

The voting protocol never chooses the same option during re-allocation in this scenario. This can be explained by the agents' relatively close efforts as well as increased social influences. The agents' utilities are similar for all options. Small differences over time, caused by increased social influences, will therefore lead faster to another voting outcome. This is amplified by the increased theory of mind influences. [62] shows figures of these changes in effort over time.

The statistical results in Table 8 show that the absolute execution time, safety incidents, social welfare and percentile deviation of man-hours are all statistically significant better for voting than for team lead decision-making. The mediated feedback protocol, however does not show significant better results for both time parameters or safety incidents, but does for social welfare and percentile deviation of man-hours.

8.4.4. SC-SOC Variations: Results

The results of the three additional scenarios are elaborated on in this section. First, we will discuss the results of the scenarios involving one new team member (SC-NEW-1) and the scenario with three new team members (SC-NEW-3). Table 9 presents the summary statistics. The statistical significance results compared to SC-SOC-VO can be found in Table 10. The total execution time and the absolute execution time are both significantly higher than for SC-SOC-VO, which is caused by the agents' biased trust beliefs.

Table 9. SC-SOC variations: summary statistics

		TIM [min]	SAF [-]	TAS [min]	USW [-]	Δ MH [-]	ALL [-]
SC-NEW-1	μ	450.3	7.565	1551	4.949	0.259	0.000
	σ	17.72	2.116	40.49	0.016	0.040	0.000
SC-NEW-3	μ	445.8	4.850	1524	4.967	0.278	0.000
	σ	21.67	1.712	37.26	0.005	0.029	0.000

Table 10. SC-SOC variations: test statistics

	TIM (A-Test)	SAF (A-Test)	TAS (A-Test)	USW (A-Test)	Δ MH (A-Test)	ALL (Fisher)
SC-NEW-1	0.19	0.08	0.02	1.00	0.00	0.00
SC-NEW-3	0.27	0.31	0.04	1.00	0.00	0.00

The number of safety incidents is significantly higher for SC-NEW-1 than for SC-SOC-VO. This could be caused by the high power influence of the team lead, with a low thoroughness goal, on the new mechanic. The number of safety incidents is also significantly higher for SC-NEW-1 than for the SC-NEW-3, This is due to the power relations between mechanics and the team lead. In SC-NEW-3 the new team lead has less power influence on the other mechanics.

The increase in percentile man-hours per task illustrates a lower mechanic-task fit than in SC-SOC-VO. The higher percentile deviation of man-hours for SC-NEW-1, however, shows that the team with one new member knows each other's strengths and weaknesses better than SC-NEW-3.

The mean social welfare is in both simulations smaller than for SC-SOC-VO. The simulations with new mechanics also have a higher standard deviation for social welfare. This is caused by more diverging preference profiles, which could be a sign of polarisation within the team. SC-NEW-3 has a higher social welfare than SC-NEW-1, since the three new mechanics created a new, but less strong, sub-culture.

Additionally, we have evaluated the entire main landing gear replacement task execution, involving multiple shifts (SC-SHIFTS). In 16 % of the simulations all 184 tasks were finished in time. Table 11 presents the summary statistics of this scenario. For the total main landing gear replacement, the number of completed tasks (NTA) has been evaluated. Results show that the average social welfare is lower for SC-SHIFTS than for voting, which could be caused by biases across teams or task demands in other shifts.

Table 11. SC-SHIFTS: summary statistics

	USW [-]	SAF [-]	NTA [-]
μ	4.988	52.13	182.5
σ	0.004	8.074	0.933

8.4.5. Scenario Comparison

Figure 6 shows the total execution time set out to the number of safety incidents for all single shift scenarios. Figure 7 illustrates a similar trade-off for the absolute execution time over the number of safety incidents. The blue dots represent the simulations that on average finish the required set of tasks within the shift, while the red simulations do not.

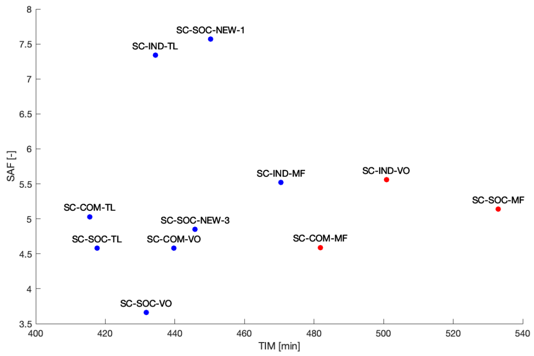


Fig. 6. TIM and SAF trade-off

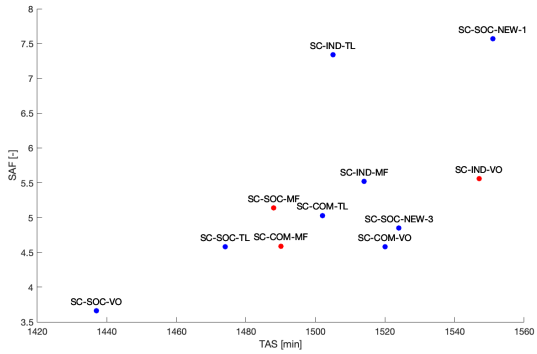


Fig. 7. TAS and SAF trade-off

Figure 6 shows that the mean values of the three simulations at the right do not finish the tasks on time, which is one for every scenario. The best performing simulations in terms of total time and safety incidents are SC-SOC-VO, SC-SOC-TL and SC-COM-TL. When minimizing the number of safety incidents, SC-SOC-VO provides the best mean values. When minimizing total execution time, SC-COM-TL provides the best results and SC-SOC-TL is somewhere in between. Figure 7 illustrates that in terms of absolute execution time, SC-SOC-VO outperforms all simulations. With the introduction of a new team member, the outcome is least favorable, illustrated by SC-NEW-1 in the upper right corner.

The scenario with social mechanics presents the best performance for the voting protocol. The team lead allocation method has a similar total task execution time for both social as well as compliant teams. In terms of absolute task execution time, the social team performs better. The mediated feedback protocol performs significantly worse than the other two methods. Only in the independent scenario the mediated protocol finishes in time. It could be the case that it performs better with divergent preference profiles.

8.4.6. Utilitarian Social Welfare Evaluation

These results made us wondering whether there is a relation between a team's social welfare and the task execution performance. This can provide an indication of whether the social welfare of an allocation can predict the global task execution performance. An initial analysis of the relation between the social welfare and other performance indicators is performed using the Pearson correlation factor, ρ [88]. The correlation factors have been assessed for the three allocation methods across the previously mentioned scenarios. The correlation factors at a significance level of 0.1 can be found in Table 12. N/A indicates a p-value lower than the significance level: ρ is not statistically significant.

Table 12. Pearson correlation factors with USW (α = 0.1)

	TIM	SAF	TAS	Δ MH	ALL
Team lead	0.23	N/A	-0.17	0.09	N/A
Voting	0.07	-0.45	-0.48	-0.66	0.06
Mediated feedback	0.27	0.09	-0.39	0.10	-0.10

For all allocation methods, a strong negative correlation exists between absolute execution time and social welfare. This indicates that the group has more knowledge about the mechanic-task fit than an individual. This can also be deduced from the significantly high and negative correlation between USW and Δ MH as well as SAF for the voting protocol. This is confirmed by the correlation for SC-SHIFTS: $\rho(USW, SAF) = -0.49$. There is a weak positive correlation, however, between total execution time and social welfare, indicating that a higher social welfare increases the total execution time. This correlation is less evident for the voting protocol and is counteracted by the correlation between USW and NTA for SC-SHIFTS: $\rho(USW, NTA) = 0.25$. This result indicates that increased social welfare decreases the total execution time for the entire main landing gear replacement.

The next section will discuss the findings from this research in a broader context and reflect on the methodology.

9. Discussion

These results show that the performance of an aircraft maintenance team changes with the social environment as well as the type of task allocation method. In Section 9.1 we will first discuss the presented results in a broader theoretical context. Section 9.2 discusses the implications of this research for aircraft maintenance practices. Limitations to this research as well as future recommendations are discussed in Section 9.3.

9.1. Decision-Making in Teams

The results of this research show that shared trust between team members increases the social welfare of an allocation, which on its turn increases the absolute execution time. This relates to the concept of shared situation awareness: "the degree to which team members have the same situation awareness on shared situation awareness requirements" [56]. Our results show that the team's shared situation awareness on the strengths and weaknesses of all other agents yields better team performance in terms of absolute task execution time.

A related concept is the shared cognition construct. Experimental research has found a positive relation between shared cognition and team performance [89]. The concept of shared cognition is however not well-defined [90]. [89] outlines four categories of 'shared' in this context: shared task specific knowledge, shared task related knowledge, shared knowledge of teammates and shared attitudes or beliefs.

Our model has demonstrated that shared knowledge of team members and shared attitudes increases team performance. Shared experienced time pressure, part of shared task related knowledge, did not lead to better task execution performance in our research. This could be caused by the underlying assumption that only the team lead tracks task execution progress. Further research could explore the impact of all agents tracking task execution progress on coordination performance. The shared cognition construct, founded in social psychology, only describes a relation between shared beliefs and team performance, rather than providing an explanation. The wisdom of crowds, a statistical concept on group decision-making, describes the phenomenon that the average judgement in a group converges to the accurate solution [7].

Empirical researchers argued that social influences undermine the wisdom of crowds effect [91]. In order for wisdom of crowds to apply, they concluded, individual judgements should be independent. Later mathematical research however showed that the impact of social influences depends on the initial opinions of the group. Groups with opinions relatively far from the truth benefit from social influences. Social influences however deteriorate the collective opinions of groups with initial opinions relatively close to the truth [92]. Another study showed that a diverse group makes better collective guesses than a group of experts, as it avoids getting stuck in locally sub-optimal solutions [93]. Biases within the group could however deteriorate the outcome, which has been shown in our simulations with the introduction of new team members and has also been illustrated in [93].

We have shown that diversity in initial trust levels in combination with shared trust among mechanics over time increases collaborative task allocation performance. This is in line with the wisdom of crowds theory.

9.2. Implications for Aircraft Maintenance

Our research has illustrated the added value of collaborative decision-making for task allocation in aircraft maintenance. Although the team goal for high performance is shared between all mechanics, different views on safety compliance, efficiency needs and the competence of team-members have shown to be driving the performance of collaborative decision-making within the team.

The analysis of the results focused on the trade-off between safety and efficiency that drives every decision in aircraft maintenance. If a team lead has a high preference for efficiency, it will allocate tasks in the most efficient manner, however overlooking thoroughness. Yet, the team decided in all but one simulation for safer task execution. Using collaborative decision-making mechanisms, the team could provide a counterbalance to explicit preferences for either thoroughness or efficiency. The aggregation of varying priorities in collaborative decision-making provides more equity to the efficiency-thoroughness trade-off than individual decisions.

Another trade-off showed a significant difference between the absolute task execution time and the total execution time for many simulations. The decision-maker therefore needs to make a trade-off between the best allocation considering all other tasks and agents within the shift, and the best mechanic-task fit. Socially oriented teams performed best in terms of absolute task execution time. The results were however not significantly better in terms of total execution time compared to team lead decision-making or voting by compliant teams.

It was found that a mediated feedback automated negotiation method provided the most favourable results in terms of efficiency and safety for independent teams. Teams that value compliance with their team lead showed the best performance if tasks were allocated by the team lead. Socially oriented teams presented the most favorable results for the voting task allocation protocol.

In line with the anthropological study [3], our research indicates that the aircraft maintenance organization should encourage the sociality of teamwork. The combination of a voting protocol and a socially oriented team has provided the best results in terms of time efficiency and safety. It should be noted, however, that different sub-cultures within a team could deteriorate the voting outcome. Moreover, the voting process can take more time than team lead allocation.

Nevertheless, we should be cautious with generalized conclusions from descriptive social simulation models [94]. Our model describes the relation between several observed processes, rather than the entire system. Further research should therefore consider other aspects of the aircraft maintenance work, such as uncertain task demands, exhaustion, cognitive workload, or personal preferences.

9.3. Reflections on Methodology

The proposed model has illustrated its ability of capturing the social elements of teamwork in the task allocation process of aircraft maintenance. It considers human elements in the socio-technical aircraft maintenance system, rather than neglecting these aspects due to social complexity. The diverse, subjective trust relations between mechanics capture part of this social complexity. The developed model was able to represent the task allocation decision-making process based on trust. Moreover, our model represents the dynamics of in-group and out-group relations in groups.

The model has, however, several limitations. First of all, the model requires assumptions on initial values. Sensitivity analysis showed that the model output is sensitive to the team lead's internal competence goals. More elaborate sensitivity analysis should be performed for agents' goals as well as other parameters. Time step variables for social influence relations, theory of mind influences and time pressure adoption could change the simulation results. Real-life data should be used to validate whether the model simulates the true practise of aircraft maintenance teams. Mechanics' motivational goals could be identified using questionnaires on Self-Determination Theory. Moreover, experimental research could evaluate the performance of the three presented task allocation mechanisms in different teams.

Moreover, it should be investigated whether differences in the constructed task packages yield different outcomes. It is unknown whether the same model outcomes would hold for tasks that have less dependencies, such as a regular A-Check. In real life, team members can swap tasks between packages. It should therefore be investigated what the effect of proposing adjustments to the task packages, either before or after allocation, would be on the overall outcome.

The absolute execution time of a task is not represented in the decision-making of the agents. This created a voting outcome for the first scenario with a high mechanic-task fit, however also high execution time. The small relative additional time resulted in a high absolute additional time for large tasks. It is therefore recommended to consider the estimated man-hours for a task in agents' decision-making.

Simulations showed that the probability of a safety incident is higher for larger tasks. This is caused by the model assumption that at every time point the agent has a probability of causing a safety incident. This is not representative for the actual work and should be enhanced.

The implemented mediated feedback protocol did not perform as expected. This is caused by how we modeled agents' preferences and how the mediator creates preference profiles of other agents. The mediator requires multiple independent issues to vary proposals and therefore generalizes agents' preferences. In our model, however, the preferences are represented as one allocation option. The only preference relations our mediator could deduce is that agent A values option 1 over option 2, but no additional information is gained from this feedback. It was expected that using 60 rounds for the feedback protocol and by remembering preference relations for re-allocation, the mediator would have enough information. The results, however, indicate that enhancement is necessary. It is recommended to design a mediated feedback protocol for allocation purposes, in which dependencies between offers for different agents can be considered. The mediator would need additional coordination properties to create different preference profiles, such as agent A prefers package 1 to be allocated to agent B rather than to agent C.

Time constraints prevented us from including mechanisms to avoid collusion for the mediated feedback task allocation method. Truth revealing incentives were investigated for a slightly different protocol: the Mediated Single Text protocol [95]. They introduced for each agent a limit of mixed accepts, which are wins of an agent despite the negative feedback of other agents on this option. This means that all agents can only have a certain given advantage over time. Similar as for the voting protocol, an additional limit for the number of mixed accepts for a group can be introduced, to accommodate for group collusion. Task allocation in aircraft maintenance teams is performed repeatedly, so agents' mixed accepts could be tracked over multiple negotiations.

The model's theory of mind properties have not shown any significant impact on the simulation results. This is caused by the model assumption that agents aim for a reputation in line with their efforts. It could therefore be concluded that agents have, in general, reputations close to their efforts. Mechanics could, however, aim for a higher reputation than their current effort or could aim for a specific reputation to avoid getting assigned certain tasks. The theory of mind properties should be extended to incorporate other cognitive aspects of people's desire for specific reputations.

10. Conclusions and Future Work

The main goal of this research was to study the relationship between the social aspects of teamwork and the performance of task allocation methods in aircraft maintenance. A model has been created to represent social influences within these teams, as well as mechanics' subjective trust in others. The model has been simulated for a case study of an Airbus A310 main landing gear replacement. We simulated independent, compliant and socially oriented teams. For each team, the task allocation method was varied, either by team lead decision-making, voting or a mediated feedback protocol.

The results showed that the teams' task execution performance, in terms of time efficiency and safety, varied for the different types of teams as well as the different task allocation methods. Independent teams provided the best performance using a mediated feedback automated negotiation method. The most favorable results for compliant teams were obtained through the allocation of tasks by a team lead. Social teams presented significantly better results for the voting protocol than for the other task allocation methods.

The combination of socially oriented mechanics and task allocation through voting provided the most advantageous task execution performance for all simulations. The diversity in initial trust levels in combination with shared trust among mechanics over time increases collaborative task allocation performance. It was therefore recommended that the aircraft maintenance organization should encourage the sociality of teamwork in socially oriented aircraft maintenance teams.

The proposed model could be adapted to include more uncertain elements or explore more sophisticated voting protocols. For example, a voting protocol could be designed with more incentives for truthful bidding such as voting weights based on reputation. Moreover, uncertainty about task characteristics or task schedules can be of interest for task allocation purposes. This research has however shown that the performance of a task allocation method depends on the way members of an aircraft maintenance team make decisions.

Bibliography

1. M. Bazargan. *Airline Operations and Scheduling.* Routledge, 2010.
2. D. Dinis and A.P. Barbosa-Póvoa. *On the Optimization of Aircraft Maintenance Management.* Springer, Switzerland, 2015.
3. C. Enache. A report on an anthropological research in digitization for aircraft maintenance. unpublished manuscript. 2019.
4. A. Atak and S. Kingma. Safety culture in an aircraft maintenance organisation: a view from the inside. *Safety Science*, 49:268–278, 2011.
5. J. Van den Bergh, P. De Bruecker, J. Belien, and J. Peeters. Aircraft maintenance operations: state of the art. Retrieved March 19th, 2019 from: $https://core.ac.uk/download/pdf/34583783.pdf$., 2013.
6. G. Weiss. *Multiagent systems: a modern approach to distributed artificial intelligence.* The MIT Press, Cambridge, Massachusetts, 1999.
7. J. Surowiecki. *The Wisdom of crowds: why the many are smarter than the few and how collective wisdom shapes business, economies, societies and nations.* Doubleday; Anchor, 2004.
8. H. Van Dyke Parunak, R. Savit, and R. L. Riolo. Agent-based modeling vs. equation-based modeling: a case study and users' guide. In *International Workshop on Multi-Agent-Systems and Agent-Based Simulation*, pages 10–25. Springer, 1998.
9. E. Bonabeau. Agent-based modeling: Methods and techniques for simulating human systems. In *Proceedings of the National Academy of Sciences 2002*, pages 7280–7287, May 2002.
10. R.K. Sawyer. Interpreting and understanding simulations: The philosophy of social simulation. In Bruce Edmonds and Ruth Meyer, editors, *Simulating Social Complexity: A Handbook.* 2013.

11. A. Cheung, W.H. Ip, and D. Lu. Expert system for aircraft maintenance services industry. *Journal of Quality in Maintenance*, 11:348–358, 2005.
12. J. Beliën, B. Cardoen, and E. Demeulemeester. Improving workforce scheduling of aircraft line maintenance at sabena technics. *Journal on Applied Analytics*, 42:352–364, 2012.
13. H. K. Alfares. Aircraft maintenance workforce scheduling:a case study. *Journal of Quality in Maintenance Engineering*, 5:78–89, 1999.
14. G. Quan, G. W. Greenwood, D. Liu, and S. Hu. Searching for multiobjective preventive maintenance schedules: combining preferences with evolutionary algorithms. *European Journal of Operational Research*, 177:1969–1984, 2007.
15. D. Bertsimas, S. Gupta, and G. Lulli. Dynamic resource allocation: a flexible and tractable modeling framework. *European Journal of Operational Research*, 236:14–26, 2014.
16. J. Brimberg and W.J. Hurley. Scheduling workers in constricted area. *Naval Research Logistics*, 43:143–149, 1996.
17. H. Zhaodong, C. Wenbing, X. Yiyong, and L. Rui. Optimizing human resources allocation on aircraft maintenance with predefined sequence. In *2010 International Conference on Logistics Systems and Intelligent Management*, volume 2, pages 1018–1022, 2010.
18. A. Stranjak, M. Ebden, P.S. Dutta, and A. Rogers. A multi-agent simulation system for prediction and scheduling of aero engine overhaul. pages 81–88, 2008.
19. F. Qiang and S. Bo. A multi-agent based intelligent configuration method for aircraft fleet maintenance personnel. *Chinese Journal of Aeronautics*, 27: 280–290, 2014.
20. N. M. Paz and W. Leigh. Maintenance scheduling: Issues, results and research needs. *International Journal of Operations Production Management*, 14:47–69, 1994.
21. R. Dekker. Applications of maintenance optimization models: a review and analysis. *Reliability Engineering and System Safety*, 51:229–240, 1996.
22. P. Callewaert, W.J.C. Verhagen, and R. Curran. Integrating maintenance work progress monitoring into aircraft maintenance planning decision support. *Transportation Research Procedia*, 29:58–69, 2018.
23. S. Fatima, S. Kraus, and M. Wooldridge. *Principles of Automated Negotiation*. Cambridge University Press, Cambridge, UK, 2014.
24. X. Zheng and S. Koenig. K-swaps: Cooperative negotiation for solving task-allocation problem. pages 373–379, 2009.
25. Y. Wang, Y. Xu, and X. Zhang. Task-allocation algorithm for collaborative design based on negotiation mechanism. In *2009 13th International Conference on Computer Supported Cooperative Work in Design*, pages 102–106, 2009.
26. A. Chapman, R. Micillo, R. Kota, and N. Jennings. Decentralised dynamic task allocation: A practical game–theoretic approach. pages 915–922, 2009.
27. Y. Kong, M. Zhang, and D. Ye. A negotiation method for task allocation with time constraints in open grid environments. *Concurrency and Computation: Practice and Experience*, 27, 2014.
28. Y. Chevaleyre, P. E. Dunne, U. Endriss, J. Lang, M. Lemaître, N. Maudet, J. Padget, S. Phelps, J. A. Rodríguez-Aguilar, and P. Sousa. Issues in multiagent resource allocation. *Informatica (Slovenia)*, 30:3–31, 2005.
29. S. Khan and I. Ahmad. Non-cooperative, semi-cooperative, and cooperative games-based grid resource allocation. volume 2006, 2006.
30. U. Endriss, N. Maudet, , F. Sadri, and F. Toni. Negotiating socially optimal allocations of resources. *Journal of Artificial Intelligence Research*, 25, 2006.
31. Gregory E. Kersten and Hsiangchu Lai. Negotiation support and e-negotiation systems: An overview. *Group Decision and Negotiation*, 16:553–586, 2007.
32. H. Gimpel. *Cognitive Biases in Negotiation Processes*. Springer, Berlin, 2008.
33. B. Edmonds and R. Meyer. Introduction. In B. Edmonds and R. Meyer, editors, *Simulating Social Complexity: A Handbook*. 2 edition, 2013.
34. A. Sharpanskykh and R. Haest. An agent-based model to study compliance with safety regulations at an airline ground service organization. *Applied Intelligence*, 45:881–903, 2016.
35. D. Passenier, C. Mols, J. Bim, and A. Sharpanskykh. Modeling safety culture as a socially emergent phenomenon: a case study in aircraft maintenance. *Computational and Mathematical Organization Theory*, 22:487–520, 2016.
36. V. Dignum. Assessing organisational design. In B. Edmonds and R. Meyer, editors, *Simulating Social Complexity: A Handbook*. 1 edition, 2013.
37. D. Hales. Group reputation supports beneficent norms. *Journal of Artificial Societies and Social Simulation*, 5:1–4, 2002.
38. V. Palmer. Simulation of the categorization-elaboration model of diversity and work-group performance. *Journal of Artificial Societies and Social Simulation*, 9:1–3, 2006.
39. A. Grow, A. Flache, and R. Wittek. An agent-based model of status construction in task focused groups. *Journal of Artificial Societies and Social Simulation*, 18:4, 2015.
40. J. Sabater and C. Sierra. Regret: A reputation model for gregarious societies. In *Proceedings of the Fourth Workshop on Deception, Fraud and Trust in Agent Societies, Montreal, Canada*, pages 61–69, 2001.
41. B. Dunin-Keplicz and R. Verbrugge. *Teamwork in Multi-Agent Systems*. Jon Wiley and Sons, Hoboken, New Jersey, 2010.
42. F. Klügl and A. Bazzan. Agent-based modeling and simulation. *AI Magazine*, 33:29–40, 09 2012.
43. N. Forrnara. *Interaction and Communication among Autonomous Agents in Multiagent Systems*. PhD thesis, 2013.
44. P. Davidsson. Agent based social simulation: A computer science view. *Journal of Artificial Societies and Social Simulation*, 5, 2002.
45. P.-O. Siebers and F. Klugl. What software engineering has to offer to agent-based social simulation. In B. Edmonds and R. Meyer, editors, *Simulating Social Complexity: A Handbook*. 2 edition, 2013.
46. E. Norling, B. Edmonds, and R. Meyer. What software engineering has to offer to agent-based social simulation. In B. Edmonds and R. Meyer, editors, *Simulating Social Complexity: A Handbook*. 2 edition, 2013.
47. A. Nowak, M.E. Miller, and R.R. Vallacher. *Social Influence and Group Dynamics*. Wiley & Sons, 2003.
48. V. Cahill, E. Gray, J. Seigneur, C. Jensen, Y. Chen, B. Shand, N. Dimmock, A. Twigg, J. Bacon, C. English, W. Wagealla, S. Terzis, P. Nixon, G. Di Marzo Serugendo, C. Bryce, M. Carbone, K. Krukow, and M. Nielson. Using trust for secure collaboration in uncertain environments. *IEEE Pervasive Computing*, 2:52–61, 2003.
49. E.L. Deci and R.M. Ryan. *Intrinsic Motivation and Self-Determination in Human Behavior*. Springer, Boston, MA., 1985.
50. E.L. Deci and R.M. Ryan. The general causality orientations scale: Self-determination in personality. *Journal of Research in Personality*, 19:109–134, 1985.
51. A.M. Colman. *A Dictionary of Psychology*. Oxford University Press, 2015.
52. R.B. Cialdini and N.J. Goldstein. Social influence: Compliance and conformity. *Annual Review of Psychology*, 55:591–621, 2004.
53. D. Levi. *Social Influence and Power*. SAGE Publications, 2007.
54. B.H. Raven. A power/interaction model of interpersonal influence: French and raven thirty years later. *Journal of Social Behavior & Personality*, 7:217–244, 1992.
55. G. Deffuant, D. Neau, F. Amblard, and G. Weisbuch. Mixing beliefs among interacting agents. *Advanced Complex Systems*, 3:87–98, 2002.
56. M.R. Endsley. Toward a theory of situation awareness in dynamic systems. *Human Factors Journal*, 37:32–64, 1995.
57. D. Rousseau, S. Sitkin, R. Burt, and C. Camerer. Not so different after all: A cross-discipline view of trust. *Academy of Management Review*, 23:393–404, 1998.
58. R. Bachmann. Trust, power and control in transorganizational relations. *Organization Studies*, 22:337–365, 2001.
59. S. D. Ramchurn, T. Dong Huynh, and N. R. Jennings. Trust in multi-agent systems. *Knowledge Engineering Review*, 19:1–25, 2004.
60. G. Cvetkovich, M. Siegrist, R. Murray, and S. Tragesser. New information and social trust: Asymmetry and perseverance of attributions about hazard managers. *Risk Analysis*, 22:359–367, 2002.
61. D. Kahneman and A. Tversky. Prospect theory: An analysis of decision under risk. *Econometrica*, 47:263–291., 1979.
62. E. de Winkel. An agent-based social simulation approach to task allocation in aircraft maintenance teams. Master's thesis, Delft University of Technology, The Netherlands, 2020.
63. M. R. Andersson and T. W. Sandholm. Contract types for satisficing task allocation: Ii experimental results. *AAAI Technical Report*, 1998.
64. American Psychological Association. *APA Dictionary of Psychology*. American Psychological Association, 2015.
65. E. Hollnagel. *The ETTO Principle: Efficiency-Thoroughness Trade-Off: Why Things That Go Right Sometimes Go Wrong*. CRC Press, London., 2009.
66. L. Legault. *The Need for Competence*, pages 1–3. Springer International Publishing, 2017.
67. M. Csikszentmihalyi. *Beyond boredom and anxiety*. Jossey-Bass, 2000.
68. Effort. In cambridge dictionary. Retrieved 05/04/2020 from: `https://dictionary.cambridge.org/dictionary/english/effort`.
69. T. Bosse, F. Both, M. Hoogendoorn, S.W. Jaffry, R. Van Lambalgen, R. Oorburg, A. Sharpanskykh, J. Treur, and M. De Vos. Design and validation of a model for a human's funcational state and performance. *International Journal of Modeling, Simulation, and Scientific Computing*, 2:413–443, 2011.
70. T. Mussweiler. Comparison processes in social judgment: Mechanisms and consequences. *Psychological Review*, 110:472–489, 2003.
71. A. Tversky and D. Kahnemann. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 5:297–323, 1992.
72. H.I. Abelson. *Persuasion: How Opinions and Attitudes Are Changed*. Springer Publishing, New York, 1959.
73. C. Anderson and A. Shirako. Are individuals' reputations related to their history of behavior? *Journal of Personality and Social Psychology*, 94:320–333, 2008.
74. O. Sharpanskykh and J. Treur. Group abstraction for large-scale agent-based social diffusion models with unaffected agents. In *Proceedings of the 14th International Conference on Principles and Practice of Multi-Agent Systems, PRIMA'11*, pages 129–142. Springer, 2011.
75. M. Farhangian, M. Purvis, M. Purvis, and T.B.R.Savarimuthu. Agent-based modeling of resource allocation in software projects based on personality and skill. In *International Workshop on Multiagent Foundations of Social Computing*, 2015.
76. E.H. Clarke. Multipart pricing of public goods. *Public Choice*, 11:17–33, 1971.
77. E. Ephrai and J.S. Rosenschein. The clarke tax as a consensus mechanism among automated agents. In *AAAI-91 Proceedings*, 1991.
78. R. Aydogan, K.V. Hindriks, and C.M. Jonker. *Multilateral Mediated Negotiation Protocols with Feedback*. Springer, Tokyo, 2014.
79. L.J. Byom and B. Mutlu. Theory of mind: mechanisms, methods and new directions. *Frontiers in Human Neuroscience*, 7:413, 2013.
80. B. Latane. The psychology of social impact. *American Psychologist*, 4:343–356, 1981.

81. A. Nowak, J. Szamrey, and B. Latane. From private attitude to public opinion: A dynamic theory of social impact. *Psychological Review*, 97:362–376, 1990.
82. R.G. Sargent. Verification and validation of simulation models. In *Proceedings of the 2009 winter simulation conference*, 2009.
83. L. Bjerregaard. *Courting The Next Generation Of MRO Workers*. Retrieved December 9th, 2019 from: $https://www.mro-network.com/training/courting-next-generation-mro-workers.$, 2018.
84. B. Mullen, J.F. Dovido, C. Johnson, and C. Copper. In-group-out-group differences in social projection. *Journal of Experimental Social Psychology*, 28: 422–440, 1992.
85. I. Lorscheid, B. O. Heine, and M. Meyer. Opening the 'black box' of simulations: Increased transparency and effective communication through the systematic design of experiments. *Computational and Mathematical Organization Theory*, 18:220–62, 2012.
86. A. Vargha and H.D. Delaney. A critique and improvement of the cl common language effect size statistics of mcgraw and wong. *Journal of Educational and Behavioral Statistics*, 25(2):101–132, 2000.
87. R.A. Fisher. On the interpretation of x^2 from contingency tables, and the calculation of p. *Journal of the Royal Statistical Society*, 85:87–94, 1992.
88. K. Pearson. Notes on regression and inheritance in the case of two parents. *Proceedings of the Royal Society of London*, 58:240–242, 1895.
89. J. Cannon-Bowers and E. Salas. Reflections on shared cognition. *Journal of Organizational Behavior*, 22:195–202, 2001.
90. M.A.Hogg and R.S. Tindale. *Blackwell handbook of Social Psychology: Group Processes*. Blackwell, Massachusetts, 2001.
91. J. Lorenz, H. Rauhut, F. Schweitzer, and D. Helbing. How social influence can undermine the wisdom of crowd effect. In *Proceedings of the National Academy of Sciences of the United States of America*, volume 108, 2011.
92. P. Mavrodiev, C. Tessone, and F. Schweitzer. Effects of social influence on the wisdom of crowds. In *Proceedings of the Conference on Collective Intelligence*, 2012.
93. L. Hong and S.E. Page. Groups of diverse problem solvers can outperform groups of high-ability problem solvers. In *Proceedings of the National Academy of Sciences of the United States of America*, 2004.
94. B. Edmonds. Different modelling purpooses. In B. Edmonds and R. Meyer, editors, *Simulating Social Complexity: A Handbook*. 2 edition, 2013.
95. M. Klein, P. Faratin, H. Sayama, and Y. Bar-Yam. Negotiating complex contracts. *Group Decision and Negotiation*, 12:111–125, 2003.

II

Literature Study

The literature study has already been graded

1
Introduction

Digitization is currently the main aspiration of many large organizations. In the present-day digital age, it is commonly believed that technology could be an essential ingredient for a more efficient [6], faster [7] and eventually more profitable company [8]. If this is not enough to start a company's 'Digital Transformation' right away, consulting companies stress that digitization is otherwise necessary for companies in order to keep up with their competitors [9].

So it is no surprise that in the increasingly competitive airline industry, digitization has been airlines' key focus in order to enhance their operational efficiency. In the past many processes in the aircraft industry have been optimized with the help of technology, such as the optimization of flight routes [10], airline network structures [11], flight operations [12] or crew schedules [13]. Only recently, tighter profit margins in combination with an increased complexity of aircraft (systems) drove the need for aircraft maintenance companies to uplift their maintenance operations as well, in order to increase their capacity as much as possible [14].

It is generally understood that the present-day challenges of digitization efforts are not about the technology itself, but revolve around the technology's interaction with humans. This relates to the field of socio-technical research, which aims at increasing the understanding of social processes in relation to technology. Ropohl [15] described the understanding of this relationship between humans and technology to be crucial in order to "shape both the technical and social conditions of work, such that efficiency and humanity would not contradict one another [15]. Many organizations as well as their consultants are currently aware of the fact that, as Poole and DeSanctis [16] state, "human use makes a technology what it is". Nevertheless, recommendations for problems with digitization, in which technologies appeared not to be aligned with their human use, all provide a similar answer: increase the human will to change, human behavioural change, human adaptation and so on [6–9].

In a recent anthropological research at a large aircraft maintenance organization, it was argued that the assumption of the need for human behavioural change subordinate to technological change is unfounded and in some cases untrue. Jeroen van den Hoven, Professor in Ethics at Delft University of Technology, argued in an article in De Volkskrant that the digital age requires a new way of looking to these problems [17]. An importance research field for this new perspective is complexity science, which is characterized by non-linear, dynamic and interconnected relationships [18] and aims at collecting theories from different disciplines [19]. Complex socio-technical system research is one of the multi-disciplinary approaches within complexity science. This research aims at contributing to the body of research in this field in order to increase the understanding of socio-technical systems, in particular for aircraft maintenance applications. An increased understanding of these socio-technical systems could provide more valid insights into the issues with digitization and create a base for more founded recommendations to improve our socio-techncial systems.

1.1. Literature Research Scope

Socio-technical systems are rather complex. It is therefore necessary to scope this research to one of the digitization processes in aircraft maintenance. Experts in the aircraft maintenance field recommended to focus on task allocation processes for task execution. This is because of three reasons. First, task allocation is a highly dynamic process. Second, social structures play a large role in these task allocation procedures in aircraft maintenance organizations. Furthermore, there is a constant interaction between the task allocation system (the technology) and the mechanics (humans). All these aspects make task allocation in aircraft maintenance of interest for socio-technical research.

The goal of this literature research is to gain a better understanding of the current practises in the allocation of tasks within aircraft maintenance and how these efforts could be supported by technology. This is done by assessing literature through Google Scholar, involving (parts) of the terms 'task allocation in aircraft maintenance', and the other identified research areas presented later. Furthermore, relevant journals have been evaluated for topics of interest, such as the "Journal of Artificial Societies and Social Simulation" or "Artificial Intelligence". Finally, several relevant text books have been studied, such as Fatima et al. [20], Shoham and Leyton-Brown [21] or Helbing and Balietti [22]. An elaborate overview of all considered literature can be found in the Bibliography.

1.2. Literature Research Structure

The structure of this report is as follows. Firstly, a literature review into the domain of task allocation for aircraft maintenance is necessary. Chapter 2 therefore provides an overview of the literature available in this domain. Besides, a potential case study is briefly described. The chapter concludes with the literature gaps that have been found during the domain research. These literature gaps shaped the rest of the research areas that have been looked in to for this report. This is outlined in Figure 1.1 below. Three main literature gaps were found: a lack of (flexible) bottom-up approaches, a lack of short-term planning and a lack of the social aspects of maintenance work. That is why more research is performed in the available approaches to incorporate these three aspects in a new research project on task allocation for aircraft maintenance.

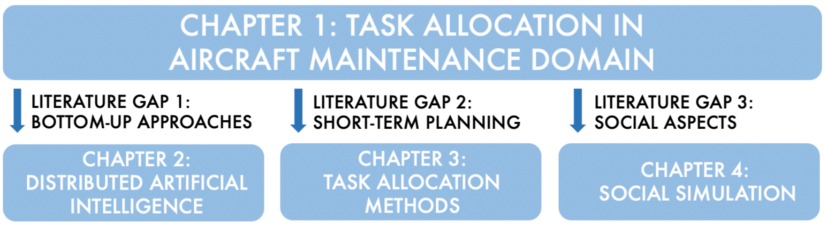


Figure 1.1: Literature review structure and relevance

In Chapter 3 literature on bottom-up modeling will be explored. Distributed Artificial Intelligence is the main bottom-up modeling approach and can provide more insights in bottom-up model design. Chapter 4 will provide an elaborate overview on the literature in task allocation procedures using bottom-up approaches in general. This is related to the second gap in literature: a lack on short-term planning. Task allocation procedures are rare in literature on aircraft maintenance management and therefore a more elaborate literature research into task allocation methods in general will be executed. The third gap touches upon the social aspects of aircraft maintenance and introduces the research area of social simulation. Social simulation is a modeling approach for social structures and factors and is further explored in Chapter 5. This chapter provides an insight in applicable social factors for task allocation in aircraft maintenance and how these social aspects could be modeled. It should be noted that in every chapter the three focus areas (bottom-up approaches, short-term planning and social simulation) are key throughout the entire literature research. For example, social factors are also considered in the chapter on negotiation for task allocation in Chapter 4. Chapter 5 also focuses mostly on the use of bottom-up approaches for social simulation. This is necessary to bridge the gap between these different literature gaps in the task allocation methods for aircraft maintenance and eventually come up with a research proposal that aims to integrate these three approaches. The research proposal following the conclusions in Chapter 6 is provided in Chapter 7.

2
Task Allocation in Aircraft Maintenance

Maintenance management in industrial application has been transformed significantly during the past decade [23]. In the past, maintenance was considered to be an inevitable part of production. However nowadays, most companies view maintenance as an important element of their business strategy [23]. According to Pintelon and Parodi-Herz [23], a reason for this changing perspective is the increasing competition across all industrial sectors, which asks for the optimization of all processes across the supply chain. Another cause is the large-scale introduction of more automatic and technological products, that are more demanding in terms of maintenance due to their complexity and criticality [23].

This new perspective led to an increasing demand for structuring and optimizing the maintenance process. While the main purpose of maintenance is to guarantee a higher reliability and availability of installations, the right allocation of resources (personnel, spares and tools) and deciding on a suitable combination of maintenance actions have become leading topics within maintenance research [23].

This is also the case for aircraft maintenance practises [14]. An important challenge in aircraft maintenance is to decide which maintenance actions should be executed at what moment in time. In the aircraft industry these decisions mostly revolve around three types of maintenance actions: corrective maintenance, preventive maintenance and condition-based maintenance. There has been quite some research into that decision-making process [24]. Yet in this research the focus will be on the allocation of resources, most importantly personnel, which is also intertwined with spares, tools and other resources. The concept of aircraft maintenance management revolves around the planning and scheduling of these aircraft maintenance activities. The different aspects of aircraft maintenance management will be elaborated on in the next section.

2.1. Aircraft Maintenance Management

Aircraft maintenance management is defined by Dekker [25] as the ”combination of all technical and associated administrative actions intended to retain an item or a system, or restore it, to a normal state in which it can perform its required function”. A general accepted framework for aircraft maintenance management has been developed by Dinis and Barbosa-Póvoa [14]. According to Dinis and Barbosa-Póvoa [14], aircraft maintenance management consists of three sub-problems:

- Capacity planning of manpower to face uncertain demand
- Spare parts forecasting and inventory management
- Task scheduling and resource allocation

Capacity planning refers to the planning phase, where the amount of manpower needed to face future demand is estimated. Similarly, inventory management and spare parts forecasting is needed to ensure that the right amount of resources is present to perform the maintenance tasks. Task scheduling and resource allocation focus on optimal scheduling of maintenance tasks , based on available resources.

These scheduled maintenance tasks then need to be allocated to particular mechanics. This is a dynamic process, with for example the arrival of unscheduled maintenance tasks or unforeseen problems that arose during task execution. Dinis and Barbosa-Póvoa [14] focused mostly on the strategic and tactical problems within aircraft maintenance, while the operational phase is of interest for the allocation of personnel to tasks. That is why for this literature research Dinis and Barbosa-Póvoa [14]'s framework was extended, covering the three problems described by Dinis and Barbosa-Póvoa [14] as well as maintenance management challenges on operational level. This framework can be found in Figure 2.1. It is important to note that there is no systematic and integrated methodology to solve these sub-problems all together and integrate the strategic, tactical and operational maintenance phases in an all-encompassing manner [14].

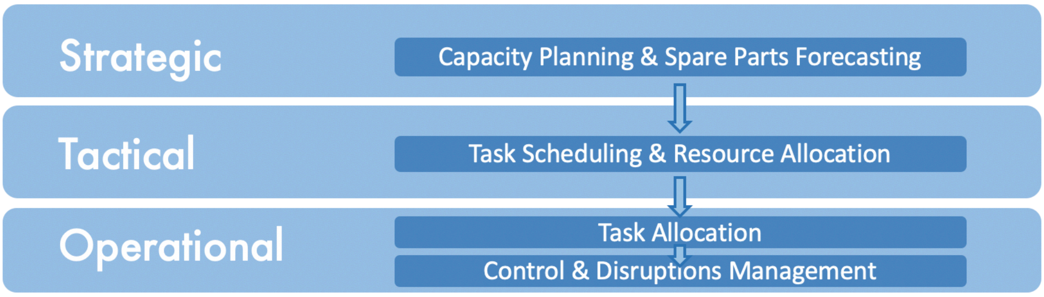


Figure 2.1: Aircraft maintenance management framework

This literature research focuses on the operational maintenance planning phase, specifically task allocation. However, current research within task scheduling and resource allocation will also be explored, since the integration of these two levels of decision-making can be of importance. Besides, task scheduling has been quite extensively researched and bears similarities to task allocation processes. Similarly, disruptions management and task allocation are interrelated, since the dynamic nature of task allocation partly originates from unexpected disturbances. So, an overview of some relevant research into disruptions management and operational control will be provided as well.

2.2. Task Scheduling and Resource Allocation

Most research on the planning of maintenance tasks revolves around task scheduling. Paz and Leigh [26] explain task scheduling as "how, when and where maintenance work is performed" and stress that human resources increase the costs of a product extensively. Besides, human resources are the most variable and relatively difficult to control. That is why optimal scheduling plays a major role in the productivity of the workforce [26]. The Cambridge Dictionary refers to resource allocation as the process of dividing resources within an organization, such as money or skills. In the case of aircraft maintenance, this mostly refers to facilities and tools. Resource allocation and task scheduling are interdependent, since task scheduling does not make sense without knowledge about the availability of the required resources. Coolen [27] refers to three main types of problems in literature, that are applicable to maintenance task scheduling and resource allocation within aircraft maintenance:

- Job Shop Scheduling Problem (JSSP): aims at determining a schedule of jobs that have specific sequences in a multi-machine environment [28].
- Resource-Constraint Project Scheduling Problem: Aims at scheduling tasks such that precedence and resource constraints are obeyed and the total makespan is minimized [29].It assumes that tasks have a finite required resource capacity, which is predefined, known and constant over time.
- Resource Allocation Problem: Aims at scheduling tasks including precedence relations between resources for a specific activity that requires multiple resources in a specific order. This is very similar to the resource-constraint problem, but now the sequencing of tasks is emphasized, instead of the distribution of resources to the tasks to be performed [14].

The goal of the aforementioned problems is to schedule tasks in an optimal way, taking into account different constraints, such as sequences in tasks, required resources for tasks, or sequences of the required resources. However in task allocation, the focus is on how mechanics split up tasks into sub-tasks and divide them among each other [30]. It is therefore assumed that the task schedule is already (to a certain degree) decided upon before task allocation starts. The next section will present an overview of the literature available for task allocation in aircraft maintenance.

2.3. Task Allocation

Baron [31] refers to task allocation as ”the way that tasks are chosen, assigned, and coordinated”. Research into the process of allocating tasks among mechanics within aircraft maintenance is marginal [32]. However, there is more research available on workforce scheduling within aircraft maintenance. Workforce scheduling, in contrast to task scheduling and resource allocation, takes mechanics as the foundation for optimizing the maintenance process. That is why research into workforce scheduling, which sometimes also incorporates (aspects of) task allocation, will be evaluated below.

2.3.1. Workforce Scheduling and Allocation

A model for workforce scheduling was proposed by Beliën et al. [33], specifically for line maintenance practices. A mixed-integer linear program is used to solve for every promising combination of team size and weeks in the roster cycle. The model does not account for the variational nature of aircraft maintenance and therefore introduced several safety factors to ensure the system’s capacity also in unforeseen circumstances [33]. So the main limitation of this model is that it does not cover the operational phase of aircraft maintenance and therefore neglects the dynamic nature of aircraft maintenance. Besides, the model does not consider the process of allocating tasks within scheduled teams.

A similar case study was performed by Alfares [34], at airline Saudi Aramco, for optimizing work schedules and man power distribution of the company’s aircraft maintenance personnel. An optimal maintenance workforce schedule was determined to satisfy growing labor requirements with minimum costs, using an integer linear programming model. The results of this model were discussed with management to change the schedule in such a way that practical constraints regarding working hours as well as other preferences of the workforce were taken into account [34]. This was an attempt to consider mechanics’ preferences to some extend, but the main objective was to develop an optimal schedule in terms of (personnel) costs, which was leading in the decision-making process.

Another study considered preferences for workforce scheduling within a linear programming model for the allocation of tasks. This has been done by Quan et al. [35] in an optimization model for preventive maintenance scheduling. The multi-objective model used an evolutionary algorithm, aiming at minimizing labor costs as well as carrying out tasks in time. A notable assumption in this model is that the preferences that are taken into account are assumed to be the manager’s preferences, instead of the preferences of mechanics themselves. Another limitation is that only two levels of skills are considered in the model. However, skill levels are important drivers for task allocation within aircraft maintenance, and vary from mechanic to mechanic and task to task. Section 2.3.2 will dive deeper into skill diversity and licence requisites within aircraft maintenance.

Like most scheduling and task-allocation methods, the model proposed by Quan et al. [35], assumes that supplies and tools are always available. In an attempt to steer clear of this common assumption, Bertsimas et al. [36] developed a binary optimization framework for resource allocation within aircraft maintenance for both job scheduling and maintenance scheduling, explicitly considering flexibility. The model was optimized for the two most applicable objective functions within aircraft maintenance, the makespan (total completion time of all tasks) and minsum (average completion time per task) [36]. One of the main limitations of this model is the computational efficiency. With some extra functions, reducing the size of formulations and by adjusting time windows to reduce the search space, the authors were able to create a model that needs a run-time of 10 minutes at most.

A different approach was taken by Brimberg and Hurley [37], who developed a method for scheduling personnel for aircraft maintenance where physical space is constricted, such as the aircraft cockpit. Unfortunately, precedence between tasks is not considered in this model. This approach of taking into account the maximum amount of mechanics that fit in a physical space is however relevant to task allocation with limited resources. The overall objective of this model is to minimize the total makespan of all tasks, which is mostly constrained by a lack of physical space in and around the aircraft [37].

2.3.2. Mechanic Skills and Licences

This section will provide an overview of the formal licences within aircraft maintenance, as well as literature on workforce scheduling and task allocation specifically based on skills and licences. This is a key aspect of task allocation, as only particular mechanics are allowed to execute specific tasks and are therefore the only ones that should be assigned to that specific task.

The International Civil Aviation Organization (ICAO) has prescribed the licensing of aircraft maintenance engineers [38]. In Europe, however, the European Aviation Safety Agency (EASA) issues these licences. They maintain five main categories [39]:

- *Cat. A*: Allows for signing off certain routine maintenance tasks.
- *Cat. B1*: Incorporates the Category A licence and additionally allows for issuing Certificates of Release to Service, and maintenance of the aircraft structure, mechanics, electronics, avionics and powerplant.
- *Cat. B2*: Includes issuing Certificates of Release of Service, as well as maintenance of the avionics, electronics and powerplant.
- *Cat. B3*: Allows for the same qualifications as Category B1, only without the authorization of Category A.
- *Cat. C*: Allows for base maintenance on aircraft as well as issuing Certificates of Release of Service for the aircraft after base maintenance tasks are completed and signed off.

This does not necessarily mean that only licensed mechanics can execute these particular tasks, but licensed mechanics are always obliged to sign-off these tasks and ensure that the execution of the task has been performed properly [40].

According to a literature review research by van den Bergh et al. [41] all task scheduling approaches considering different skill levels and licenses are modeled using operations research techniques. An example is a model developed by Zhaodong et al. [42], which considers different capabilities of workers using a genetic algorithm. This research particularly focuses on developing a work flow of predefined sequences to assist the optimization model. For modeling human capabilities, a binary variable, w_{ij}, was introduced for each task j per worker i. A w_{ij} equal to 1, means the mechanic is extremely capable of performing the task and a 0 indicates the opposite. A limitation of this model is that a complete overview of all inter-dependencies between tasks is needed before scheduling can be performed, which is almost impossible to establish in real maintenance practises.

Workers' capabilities and skills are also considered in a model developed by Dietz and Rosenshine [43]. This model aims at optimizing the level of specialization of a maintenance workforce, including all types of training and wage costs, while satisfying manpower constraints. Task allocation is not considered in this research, but the focus is rather on strategic decision-making.

2.4. Operational Control and Disruptions Management

Most research on disruptions management within the aviation industry focuses on disruption management for airlines [44]. This relates to disruptions within maintenance practises, since a delay in maintenance execution results in a disruption of the aircraft's intended flight schedule. Next to aircraft delay, other considerations play a role for the operational control of aircraft maintenance operations, such as the absence of spare parts, incoming unscheduled maintenance tasks or a lack of manpower. The purpose of reviewing operational control in this research is not to present an all-encompassing overview of methods for operational control and disruptions management in aircraft maintenance, but to give the reader an idea of how the dynamic aspects of aircraft maintenance planning, and preferably task allocation, could be managed.

Research into the operational control of aircraft maintenance quickly leads to the subject of Decision Support Systems. A simple definition of Decision Support System (DSS) is presented by Dekker and

Scarf [45]: ”a system that supports the choice between alternatives”. Another generally accepted definition on Decision Support Systems was introduced by Sprague [46], which argued that Decision Support Systems:

- Focus on unstructured, unspecified, complex problems.
- Use analytic techniques or models to evaluate data on specific problems.
- Are interactive and easy to use for people on the ground.
- Serve flexibility and take into account changes in the environment.

Callewaert [24] states that there are two types of decision support systems: operational and strategic systems. The first two aspects by Sprague [46] could be considered as strategic DSS, while the latter two are more focused on the operational strength of DSS.

Operational Decision Support Systems could account for the dynamics of task allocation. A DSS for task allocation in aircraft maintenance was developed by Cheung et al. [32], using an Analytic Hierarchy Process. This tool was developed because, as Cheung et al. [32] state: ”the intuitive decisions of managers are biased and they have too limited personal experience, knowledge and perception for obtaining an optimal decision”. A limitation of this research is that the model decides per task which mechanic would be the most suitable, but does not optimize or consider the entire system. Furthermore, the authors focus on the assumption that humans are not (always) capable of judging the capabilities of their fellow colleagues.

A limitation of Decision Support Systems in general is that (most) maintenance Decision Support Systems act like a black box [25]. A DSS will only be of help when the user of the system can interpret the results, validate the calculations and convince his or her management of their value [25].

2.5. Identification of Literature Gaps

The previous sections of this chapter presented an overview of the literature in the domain of task allocation for aircraft maintenance. In order to contribute to the existing research within this field, it is key to identify the main gaps in literature. These gaps can then be further explored in the next chapters, in order to end up with a suitable research objective and method. Based on the information presented before in this chapter, the following main research gaps are recognized:

- *Lack of flexibility and bottom-up approaches*: All literature that has been found for task allocation, workforce scheduling or task scheduling used top-down approaches (mostly linear programming methods). These top-down approaches are not able to capture the dynamics of aircraft maintenance as well as the flexibility that is needed for the execution of tasks in the most efficient manner. In some models flexibility has been considered (still using a top-down approach), but the run time of these model constrains their use in real-life maintenance. Bottom-up approaches are needed to account for the dynamic nature of task allocation and incorporate flexibility.
- *Lack of research on short term planning*: Most research focuses on strategic or tactical decision-making and there is especially a lack of research on task allocation purposes. A reason for this could be the difficulty of considering the dynamics of the operational phase within optimization models. However, optimal strategic and tactical plans only pay-off when these are properly integrated with the operational plans. These operational models require an accurate representation of the availability of resources and man-power and need to be able to deal with uncertainty.
- *Lack of the mechanics’ perspective and social factors*: Only a few amount of researchers has tried to incorporate worker preferences in task allocation and scheduling. Approaches from the mechanics’ point of view or considering any social aspects of the maintenance work have not been presented. Aircraft maintenance is, however, a collective effort involving many social relations. Besides, mechanics have the local knowledge of, for example, the task execution, efficient ordering of tasks, others’ skills, but also have individual preferences for task execution, working hours or fellow team-members. If mechanics do not internalize the plans proposed by the task allocation model, the task allocation optimization process could be useless.

Most of these literature gaps are interrelated. Bottom-up approaches allow for flexibility in a system, can easily incorporate the perspective of ”lower-level” people, as well as ”lower-level” information, such as the actual availability of resources, and are specifically suitable for short-term planning, involving operational dynamics. It is believed that due to this interrelation, this research project could be addressing these three gaps all together. The next chapters will therefore explore the use of bottom-up models, task allocation and social aspects of task allocation procedures. Based on this elaborate review, the research proposal will narrow the direction in order to create a feasible research scope for a MSc. thesis project.

The three literature gaps also relate closely to issues that were observed recently at a large Maintenance, Repair and Overhaul organization (MRO) by a team of anthropologists. The next section briefly elaborates on this research, which could be a potential case study for the upcoming research project.

2.6. Case Study

This section presents the main takeaways from a study performed by three anthropologists at a large aircraft maintenance organization (MRO). They have been studying the behaviour of mechanics in the MROs hangars to uncover social rules, hierarchies and other social constructs at place. This research was initiated by the company's management, since the outcomes of a recent digital transformation did not meet expectations, and they thought the mechanics were ”digitally illiterate”. However, the anthropologist argued that this is a biased assumption and does not consider any inadequate properties of the digital system at all. The main issue with the technology currently in place, they argue, is its structure: it provides a rigid schedule that is decided upon in advance, and does not support the agile practises of aircraft maintenance task execution. Furthermore, there is distrust between mechanics and other departments, which makes collaborative improvement of the system a complex matter.

Three main recommendations are presented by the anthropologists with respect to task allocation systems. Firstly, to allow for a more agile system, *teaming protocols* should be integrated into the existing task allocation and rostering software. The anthropologists noticed that the completion of each task is a collective effort between mechanics within or across shifts. The current system in place does not allow for teaming efforts at all. Besides, the technology should allow the jointly *negotiation of solutions* to problems by mechanics, where arguments are presented in the following five categories: availability of materials (also people or tools), rules and regulations, experience with a problem, time pressure and the fact that some details are unknown. Thirdly, the technology should find a way to cope with *fragmentation*, since the team lead does not feel supported by the people of the planning stage. The technology currently in place does not assume fragmentation at all and is therefore only able to function in an utopian way.

The anthropologists call efforts of the mechanics to solve these disconnects hybrids. These hybrids are already more or less supported by the organization and should be incorporated in the wider organization of the company. An example of these hybrids is related to the way rostering is performed: the team lead first discusses rostering options with other departments. Based on these discussions, the team lead provides three to four options for rosters, which are voted upon democratically by the mechanics. The schedule is then updated in a spreadsheet and the mechanics keep the team lead informed of any changes through a WhatsApp group. This WhatsApp group also facilitates negotiation among the mechanics on shift changes. When a shift change is agreed upon by the team, it is updated in the spreadsheet and the mechanic applies for a formal shift change in the official system.

This report shows that a top-down approach to task allocation can cause problems, since it does not allow for the agility required for aircraft maintenance. A bottom-up approach could be beneficial to incorporate some of these 'hybrid' attempts as well as existing social rules in task allocation procedures. This was also one of the observed gaps in literature on task allocation in aircraft maintenance, see Section 2.5. That is why the next chapter will be focused on the topic of Distributed Artificial Intelligence, the main bottom-up modelling approach available.

3
Distributed Artificial Intelligence

As top-down approaches showed not be sufficient for the agile work environment of aviation mechanics, a bottom-up modelling approach is needed. That is why the field of Distributed Artificial Intelligence (DAI) is introduced in this chapter. Ponomarev and Voronkov [47] state that Distributed Artificial Intelligence can be defined by three main characteristics: a method for distributing tasks between agents, for distributing powers and for communication by agents. According to Kraus [48], Distributed Artificial Intelligence "aims to increase the power, efficiency, and flexibility of intelligent automated systems (agents) by developing sophisticated techniques for communication and cooperation among them". Bond and Gasser [49] argument that one of the main area's of interest for DAI is the analysis and development of mixed collections of machines and human agents.

3.1. System Classifications

Distributed Artificial Intelligence can be roughly divided in three classes [50]:

- Distributed Problem Solving, with cooperative agents aiming to solve a global problem [48]
- Multi-Agent Systems, which includes self-motivated agents that use interaction with other agents and environments to learn and make autonomous decisions [50]
- Parallel-AI, which aims to develop algorithms, languages and architectures to increase efficiency of classical AI algorithms [50]

According to Shoham and Leyton-Brown [21], an agent is considered to be self-motivated when it has its own description of which states of the world he likes, which can also be good things happening to other agents and does not necessarily mean that the agent only cares about himself. It is important to note that self-motivated agents could also join together to work towards the same joint goal [48]. The aircraft maintenance mechanics are considered to be self-motivated, since they have their own internal goals and states (although work cooperatively towards a common goal). So, that is why the next chapter will cover literature on multi-agent systems in particular.

According to Sycara [51] research in multi-agent systems covers "the study, behavior, and construction of a collection of possibly preexisting autonomous agents that interact with each other and their environments". Autonomous agents are sometimes also referred to as intelligent agents, and no general accepted definition of agents exist. Bonabeau [52] refers to agents as entities that make their own decisions in a dynamic environment. Franklin and Graesser [53] refer to an autonomous agent as a system that is situated in an environment, senses it and acts over time, aiming to achieve its own goals. Wooldridge [54] refers to an agent as a computer system present in an environment and can act in this environment, based on the designers' or users' goals, instead of being told what to do. Although the emphasis of these definitions differ, it is generally accepted that agents are: autonomous, flexible, have their own control, interact (with other agents) and are situated in an environment.

A classification for the use of modeling and simulation for multi-agent systems is provided by Davidsson [1]. The intersection of the three areas that are of importance for multi-agent systems in social context is presented in Figure 3.1. Multi-Agent Based Simulation (MABS) generally studies the use of the agent paradigm for computer simulations of complex phenomena. Social Simulation (SocSim), however, corresponds to the simulation of social phenomena using simple models with basic interactions. Social Aspects of Agent Systems (SAAS) studies social aspects such as norms and organization. that intersect between social sciences and agent-based computing. It is argued that agent-based social simulation is key for using ”agent technology to simulate social phenomena on a computer” [1].

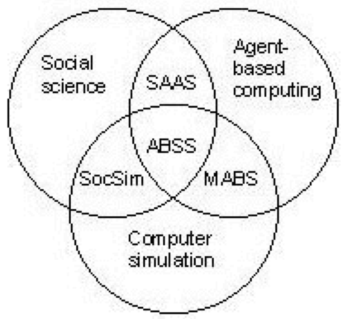


Figure 3.1: Agent-Based Social Simulation classification [1]

Agent-based social simulation is a subset of agent-based modeling and simulation (ABMS) [1]. Agent-based modeling and simulation has the goal of gaining insights into the collective behavior of agents obeying rules, typically in natural systems, and not particularly solving straightforward distributed problems, which is the case for multi-agent modeling and simulation [55].

Since in this research, the social aspects of task allocation and negotiation in aircraft maintenance are believed to be of importance, agent-based social simulation is expected to be the main modeling method. Since this is part of the wider applied agent-based modeling and simulation perspective, the next section will focus on ABMS. The application of ABMS to social simulation is elaborated on in Chapter 5. The next section will cover the general concepts of agent-based modeling and simulation in more detail and present some existing research in that area.

3.2. Agent-Based Modeling and Simulation

Agent based methods are believed to be most applicable for systems with a high level of localization as well as distribution [56]. Two decades ago, Sycara [51] stressed that the majority of agent-based research and systems in place at that time was focused on only single agents. However, currently, the application of agent-based modeling revolves around the use of multiple agents that interact and communicate [50]. Agent-based simulations generally have the goal of either providing explanation of a certain system or phenomenon, or prediction the future states of a system [57].

3.2.1. Advantages and Disadvantages of Agent-Based Modeling

These explanations are mentioned by Bonabeau [52] as one of the main advantages of the usage of agent-based modeling: it allows to capture emergent phenomena. Moreover, an agent-based model provides a natural description of a system and is flexible [52]. Furthermore, it can be easily combined with other modeling methods, which can speed up the modeling process [22].

Several concerns regarding the use of agent-based modeling can be found in literature. First, Bonabeau [52] states that the level of description remains an art more than a science and no real protocols exist for this purpose. Furthermore, it can be hard to quantify, or justify human behaviour, which can be irrational, involve subjective choices and complex psychology [52]. That is why validation of an agent-based model is generally a difficult task. Ahmad [58] stresses that since agent-based modeling is a bottom-up approach, simulating small units for a large system can be computationally expensive. However, this can be reduced by introducing so-called ’middle agents’ that speed up the communication or knowledge sharing between other agents. Another common pitfall is that the combination of a relatively easy implementation in contrast to the hard to grasp concepts often leads to improper use of agent-based modeling techniques [58].

Two similar modeling methods that involve decision-making and distributing knowledge are object-oriented programming and expert systems. Dorri et al. [50] provided a table with the results of their study on the differences of agent-based modeling with these methods. The main difference is that agents are able to base decisions on their goals and not only on inputs (object-oriented programming) and knowledge (expert systems). Expert systems have a human in the loop that is advised by the computer program, but the decisions are made by people. In object-oriented programming the actions are pre-defined by the designer of the system. The use of agents allows for a free-er and more autonomous way of simulation. But how these agents make their decisions differs from model to model: many types of agent architectures can be distinguished in literature. The next section will highlight the main categories of agents in current research.

3.2.2. Agent Decision-Making Architectures

Many different agent types and architectures have been developed. An early overview of the different types of agents was presented by Weiss [59]. He distinguished four different types of architectures: logic-based agents, reactive agents, belief-desire-intention agents and layered-architectures. A recent survey on agent decision-making by Balke and Gilbert [60] explored most literature up till then and provided a different classification of architectures. The logic-based agents, reactive agents and layered architectures, as classified by Weiss [59], are part of the production-rule systems in Balke and Gilbert [60]. Thus, an overview will be presented of the classification of agent models [60]:

- *Production Rule Systems*: Models based on behavioral if-then rules.
  - Pro: Relatively simple to understand outcomes and decision trees.
  - Con: Only based on predefined rules, which do not account for human behavior.
- *Belief-Desire-Intentions (BDI) and derivatives*: Mental states, beliefs, desires and intentions are the bases for decision-making.
  - Pro: Can deviate from if-then rules, goal-persistent, therefore dynamic.
  - Con: Assumes agents to be (bounded) rational, does not provide agent communication and explicit learning mechanisms.
- *Normative Models*: Based on norms (external factors) that influence agents decision-making.
  - Pro: Can capture external motivators instead of only internal motivators, like beliefs.
  - Con: Research covers mainly abstract representations rather than implementations.
- *Cognitive and Psychologically or Neurologically Inspired Models*: Use cognitive research as a basis for agent architecture or even structural properties of the human brain.
  - Pro: Aims at modeling the human decision-making process as it is.
  - Con: With increased realism of the decision-making process comes increased complexity, making it harder to analyze the results and have a proper functioning model.

The BDI agent model is relatively popular in the agent community [60]. Originally, the theory of belief, desires and intentions was developed by philosopher Bratman [61]. Over the years, many variations on the model have been developed, such as the emotional BDI (eBDI) [62], the beliefs-desires-obligations-intentions model (BOID) [63], which also takes norms into account, and BRIDGE, which aims to integrate social awareness of agents [64]. Sun [65] argues that social simulation researchers mostly make agent-models specifically for a particular problem, which limits realism as well as general relevance for social simulation. That is why Sun [65] claims that cognitive models are key for social simulation practises.

3.2.3. Specification and Implementation

Capturing the dynamics of a multi-agent system is important for agent-based modeling. Differential and difference equations are often used to represent dynamics in mathematical models [66]. Dynamical Systems Theory is another method for modeling the global dynamics of a system [66]. However, for agent-based modeling, the local behaviour of agents is of importance, which requires mostly qualitative, logical language [66]. Bordini et al. [67] argue that the use of formal logic allows for both specification as well as verification that is well founded and interrelated.

Dastani and Meyer [68] gathered the most leading theories and articles on agent modeling languages and their verification in a book on the specification and verification of multi-agent systems. Many logic-based methods for modeling agents were presented, mostly using temporal logic or modal logic with intentions, desires or motivations. Examples of temporal logical methods are Linear-Time Logic (LTL), Computation Tree Logic (CTL and CTL), Propositional Dynamic Logic (PDL), and Modal Logics with agent-specific concepts such as beliefs, goals and plans [69] are for example KD and KD4 [67].

Most modeling languages make use of these logics. Examples are: 3APL and 2APL [70], SimpleAPL [71], BUnity and BUpL [72], CASL [73], AgentSpeak [74], Temporal Trace Language (TTL) [75] and LEADSTO [76]. It depends on the specific requirements of the model with respect to the level dynamics as well as agent-specific properties such as beliefs, desires or intentions, which of these languages would be the most appropriate and useful.

Regarding to the implementation of an agent-based model, there are many alternatives available. Abar et al. [77] provided an overview on the state-of-the-art agent-based modeling and simulation tools available. In the early days of the development of agent-based models, conventional programming languages, such as C and Java were mainly used. However, currently, there are many existing tools available, especially for modeling and simulation in social and human sciences [77]. In order to be able to choose which tool would be most suitable, Abar et al. [77] developed a table with these tools and evaluated them on the level of effort necessary for model development and the models' scalability level.

Since the author of this research is a MSc. student, and not very familiar with agent-based modeling yet, it would be best to find an instrument that is rather easy to implement (among others: TAgentScript, AgentSheets, BehaviourComposer, FLAME, Framsticks, JAS-mine, MIMOSE, MOBIDYC, NetLogo, Scratch, SeSAm, SimSketch, StarLogo, StarLogo TNG, Sugarscape, VisualBots, VSEit). From the tools classified as easy to use NetLogo and SeSAM are presented as the most scalable ones. Next to Netlogo, Dorri et al. [50] also mentioned Anylogic, Repast and Mason as common tools for agent-based model development. According to Abar et al. [77] these tools have a high scalability level, but require moderate to complex development effort. Further research into the specific use of these simulation tools could be done when the models' purpose has been more clearly defined and a conceptual, or formal, model has been developed.

3.2.4. Verification

As in every type of model that is being developed, verification is key for ensuring that an agent system will behave as it is designed. However, it can be hard to trace the specific behaviour of a multi-agent system. Wooldridge [54] introduced the problem of ungrounded semantics, which states that it should be possible to identify what beliefs, desires and intentions of the system are driving certain system properties, to check whether the system is behaving in line with these beliefs. In their book, Dastani and Meyer [68] also presented the most recent literature on verification methods for agent-based modeling. Some of these mostly present a mathematical verification method [71, 78, 79] while others presented a more practical verification method [67, 80].

3.3. Integrative Agents

A method for using agent models in practice that is worth mentioning in this literature review is the use of integrative agent models. Integrative agents can be used in multiple ways, which can vary from the concept of adaptive information presentation, as presented in van der Mee et al. [2], a personal assistant during demanding task execution [81], or an environment that is able to prevent crime [82]. The first two examples relate to direct integration of agents with individuals, while the latter focuses on the integration of group processes. A broader futuristic vision of this concept is referred to in literature as Ambient Intelligence, where people will be constantly monitored, analyzed and supported in their doings by electronic environments [83].

Reasons for using integrative agents are their ability to coordinate fast and effectively and, most importantly, the possibility of providing information as well as guiding actions based on the circumstances [81]. With respect to task allocation, these circumstances can be for example [2]: task characteristics, human characteristics, the environment, task status, the cognitive or functional state of people. For example, in highly demanding situations, human attention and situation awareness decreases, due to an increased cognitive workload, resulting in less performance [84]. In contrast, autonomous systems can also decrease human situation awareness [85]. A solution for this is an integrative and adaptive system, that only offers help when needed [2]. An example of support by an integrative agent in dynamic task allocation, is a model that uses the environment to monitor if someone gets overloaded and then assigns tasks of that person to someone else [81].

3.3.1. Integrative Agent Architecture

Van der Mee *et al.* (2009) presented an architecture for an integrative agent model, using component-based agent design. The model consists of a domain and a control model (sometimes also referred to as ambient agent model). The domain model is a representation of the human process that is being monitored. The control model consists of two components: an analysis component, which examines states and processes based on observations and the domain model, and a support component, that proposes or produces actions for supporting the human, also based on observations and the domain model [2]. An illustrative overview of this architecture can be found in Figure 3.2. A key difference between the reasoning methods of the analysis and support models, is that the analysis model predicts future states based on the domain model, while the support model reasons from the desired future state backward to the current state.

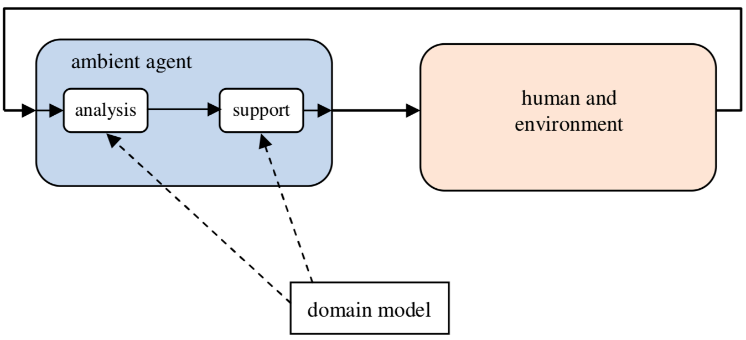


Figure 3.2: Integration of domain and control models [2]

3.3.2. Explainable Artificial Intelligence

A key aspect in the use of integrative agents, is that these agents need to be able to explain and communicate with humans in their environment. People should understand the decision-making process of an automated system to some extend in order for them to trust the system enough to let it decide for them [86]. The field of Explainable Artificial Intelligence (XAI) refers to the ability of an automated system to explain to humans what decisions are being made and, most importantly, why. Currently most research into Explainable Artificial Intelligence focuses on explanations in Machine Learning techniques, more specifically deep learning techniques [87]. This is because on one hand the recent breakthroughs in Machine Learning performance and on the other hand the in-transparent methodologies and outcomes, which ask for thorough explanations.

Nevertheless, this research is focused on Distributed Artificial Intelligence, so only the explanation of these approaches will be considered here. Some experimental research has been performed for teams of humans and agents in Mercado et al. [88], which showed that increased transparency by agents results in increased human-agent performance and increased trust levels between the two. Earlier it had been showed by Parasuraman and Riley [85], that transparent explanations were successful in preventing the abuse of automated systems. Lipton et al. [89] argue that an ideal explanation should be accurate, hold the minimum amount information possible, and should be easily be interpreted.

Recently, several methods for incorporating explanation in agent-human collaboration are presented. Firstly, Devin and Alami [90] made use of a theory of mind. In social science, theory of mind covers the ability of individuals ”to reason about the thoughts, beliefs, and feelings of others to predict behavioral responses” [91]. Devin and Alami [90] developed an agent that was able to estimate a person’s goals, plans and actions, instead of only reasoning about the humans’ environment. An implementation of this model saw an increase in efficiency for the execution of the human and agent’s shared plans. Amgoud and Prade [92] used argumentation-based approaches to explain decision-making. An advantage of this approach is that converting arguments to explanations is rather straightforward. Zhong et al. [86] introduced natural language explanations to these argumentation-based approaches, to explain why one decision is favourable over another.

Miller [93] states that social research on explanations should be considered more in Explainable Artificial Intelligence work. It is argued that human biases in the generation of explanations should be considered to improve AI-human interaction. In an extensive review, the following findings from social science are believed to be important for Explainable Artificial Intelligence, yet more or less neglected in current applications:

- *People mostly present contrastive explanations*: Instead of why someone chose option A, they will explain why it chose for option A instead of option B.
- *People select an explanation*: They never give a complete overview of the causes but select one or two reasons for an explanation.
- *People don’t refer to probabilities*: Using statistics and probabilities for an explanation is for most people unsatisfying, in contrast to using causes to explain.
- *People perform explanations in social contexts*: And are therefore based on beliefs of the explainer about the explainee’s beliefs about that situation.

The main takeaway of this paper is that explanations are dependent on the environment and the agents and people involved. This should be taken into account when using Explainable Artificial Intelligence approaches for human-agent interaction. More research on human-agent interaction can be found in Section 4.3.2, which covers the use of integrative agents for negotiation purposes.

The general approaches within multi-agent systems and agent-based modeling have been discussed in this chapter. Since task allocation in aircraft maintenance is the main focus for this literature research, the next chapter will discuss the use of task allocation methods within multi-agent systems and agent-based modeling.

4

Task Allocation Methods

Task allocation is a form of coordination, where tasks arrive dynamically and can change in intensity [31]. Coordination is the management of inter-dependencies between tasks [94]. In Figure 4.1 a breakdown of the concept of coordination in multi-agent systems is shown. Purely cooperative agents that aim at coordinating their task execution are part of multi-agent planning, whether centralized or distributed. As explained in Chapter 3, the distribution of tasks within aircraft maintenance considers self-motivated agents with common goals. However, when individual goals are not completely aligned, agents will need to negotiate in order to come to a join decision. That is why for this literature review on task allocation, multi-agent negotiation is of importance. The next sections will therefore focus on negotiation in multi-agent systems.

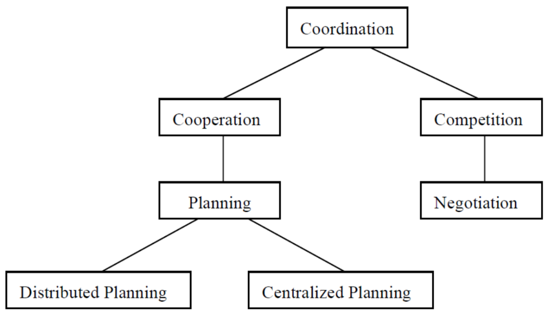


Figure 4.1: Coordination framework [3]

In literature, task allocation in multi-agent systems is also classified as: centralized task allocation, distributed task allocation or a combination of both, called combintarorial task allocation. Centralized control induces a central controller responsible for task allocation [95, 96]. Since all information is available for the controller, task allocation will be performed efficiently in small systems and communication costs are low. However, scalability is limited due to the high computational efforts and a single-point-of-failure is not favorable. When referring to Figure 4.1, it can be stated that centralized task allocation is a form of centralized planning.

Davis and Smith [97] introduced the concept of distributed task allocation in multi-agent systems and many papers have been presented on the topic since then [48, 96, 98–101]. In a distributed task allocation approach, agents only have a local view of their adjacent neighbors [102]. This has the advantage that each agent can make its own decisions, which results in a more scalable and flexible method. But with distribution, communication costs and complexity increase. An attempt to overcome this issue was performed by Krothapalli [101] to include communication costs for task allocation, but centralized task allocation was still found to be more efficient (under static conditions). Jiang and Li [103] introduced three main evaluation factors for decentralized task allocation: agent talents (resources and skills), centrality (social distance to other agents) and load-balancing of tasks between agents. dos Santos and Bazzan [100] used a swarm-intelligence approach for distributed planning of tasks and specifically group forming. A negotiation approach to account for team formation was taken by Wang et al. [98], where tasks are assigned based on people's ability, interest, load and resources.

Some researchers aim at linking centralized and distributed task allocation approaches in order to use the advantages of centralized and distributed task allocation and mitigate their disadvantages [104, 105]. An example is the use of centralized information access, while task allocation is performed through negotiation by Rahimzadeh et al. [105]. Another approach is a negotiation mechanism, such as a contract net, that allows to exchange tasks after an initial (central) task allocation [96].

In this research, information on the initial schedule and available resources could be available to all agents. However, information and beliefs about other agents' skill levels or preferences as well as information regarding task completion times is local. That is why centralized task allocation methods (using centralized planning) are not believed to be applicable for this literature review. In both the distributed as well as combinatorial task allocation methods, negotiation will be necessary because of the presence of self-motivated agents. Furthermore, negotiation is also an important factor for the communication between agents [106]. The next sections will therefore focus on negotiation, its application in agent-based modeling, and the human aspects of automated negotiation.

4.1. Negotiation Mechanisms

A negotiation is defined by Gimpel [107] as 'a non-individual decision-making process, which involves two or more parties that jointly determine outcomes of mutual interest to resolve a dispute via exchanging ideas, arguments and offers'. However, Kersten et al. [108] focuses on the iterative nature of negotiation and define it as: "an iterative communication and negotiation process between two or more participants who cannot achieve their objective through unilateral actions". An essential aspect in negotiation, as stated by Rahwan et al. [109], is the conflict of interest between agents, but also the dependence on the agreement of others to pursue an individual or common goal.

Negotiation is a widely applied research field, both within law and social sciences, economic sciences, management, as well as computer science and information systems [107]. Automated negotiation refers to negotiation performed (partly) by autonomous agents. Fatima et al. [20] consider several advantages of using automated negotiation, which includes: a higher quality of negotiation outcomes, reduced costs for negotiation processes, and cultural issues such as human stress relief. However, disadvantages are a lack of trust in automated solutions, legal considerations, incomplete models of preferences, ethical considerations and the possibility of people losing their jobs due to automation.

Several negotiation mechanisms are distinguished in literature. The main techniques are contract net protocol methods, auctions, bargaining strategies and voting protocols [106]. These techniques will be elaborated on below, with a focus on their use within task allocation procedures.

4.1.1. Contract Net Protocol

Smith [110] introduced the concept of contract nets and consequently Davis and Smith [97] introduced the contract net protocol for negotiation in multi-agent systems. The purpose of a contract net protocol is to break down a problem into sub-tasks, that are distributed among a set of agents [21]. These agents will negotiate by repeatedly contracting out assignments among themselves, where each contract involves the exchange of tasks or money. This makes the contract net protocol a many-to-many negotiation technique. Smith [110] presented six key stages for contract net protocol negotiation. These are summarized by Fatima et al. [20] in the following four main stages:

- *Recognition and announcement*: An agent decides to act as a manager and recognizes that it needs a contractor for task execution. The manager will therefore announce the contract net protocol and additional information, such as bid specification and expiration time.
- *Bidding*: The potential contractors evaluate the announcement and potentially send out a bid.
- *Bid selection and awarding*: The manager will select a bid (in the case of multiple bidders) and awards the task to the winning bidder, which is now the contractor.
- *Reporting results*: The contractor reports back to the manager when it has accomplished the task.

Decommitment of a contract was introduced by Sandholm and Lesser [111], through so-called levelled-commitment contracts. An agent can decommit from a contract by paying a decommitment penalty to the other party. They showed that the option for decommitment increases the efficiency of the system, since it allows for escaping local optima.

Sandholm [112] introduced different types of contracts for reallocating tasks: original contracts (single task contracting), cluster contracts (bundling tasks), swap contracts (exchanging tasks) or multi-agent contracts (simultaneous task exchange by multiple agents). It was found that every contract type avoids some local optima and that the combination of the four contract types will eventually reach a global optimum when agents are rational. The time for reaching this goal could however be large and local optima still exist. Experimental research found that original contracts found local optima with a higher social welfare than others when the ratio of agents to tasks is large. Cluster contracts are most favourable in terms of social welfare when the ratio of agents to tasks is small [113].

4.1.2. Auctions

An auction is a negotiation technique that uses an explicit set of rules to determine resource allocation and prices on the basis of bids made by participants [108]. Auctions always consider self-interested agents that are assumed to bid in a way to maximize their personal payoff [21]. Single-sided auctions consider one auctioneer with multiple bidders, while double-sided auctions also allow competition among auctioneers.

Kersten et al. [108] consider several characteristics to be differentiating auctions from other negotiation techniques. The first is that the rules are explicit and known beforehand to both the auctioneer and the bidder. Secondly, these rules are decisive in defining the winner, so auctioneers have no say in choosing the winner of the auction. Auction rules include: bidding rules (how bids should be formulated and communicated), allocation rules (allocation of resources on basis of submitted bids) and pricing rules (prices bidders have to pay). These rules focus mainly on the price of bids and ensure therefore either an efficient allocation or revenue maximization for the auctioneer.

Agents' valuations for an object can differ within auctions. Three types of auctions with respect to object valuations are distinguished in literature [20]: common value auctions, private value auctions and correlated value auctions. In common value auctions, the value of an object is based on the same aspect for all bidders (mostly derived from a market price). In private value auctions agents have their own independent valuation of an object. In a correlated-value auction agents have their own private values, but also consider others' valuations, in case they want to resell later.

Another feature of auctions is whether the bidders know each others' bids. An open-cry auction allows all bidders to see other bids. In a sealed-bid auction, however, agents present their bids to the auctioneer in private. The highest bidder always wins, but that could be for both its own bid (called first-price), or the second-highest bid (second-price). Besides, a one-shot auction allows only one bid, while sometimes auctions are performed in many rounds. The bidding order also changes for different types of auctions, both ascending-price as well as descending-price auctions can be used.

The traditional auction types are the English Auction, Dutch Auction, First-Price-Sealed-Bid Auction and the Vickrey Auction. Some also refer to the Japanese Auction when considering the traditional auction types [114]. In an English auction, an auctioneer raises an, initially low, price until there is only one interested bidder left. On the contrary, the Dutch auction is a descending-price auction where the auctioneer starts at a high price and keeps lowering the price until someone is willing to pay that price. The First-Price-Sealed-Bid auction is a simultaneous auction, where every bidder presents a private bid to an auctioneer, and the highest bidder wins the auction for its own bid. In the Vickrey auction, all bidders also presents private bids to the auctioneer, and the highest bidder also wins, but now for the second-highest price [115]

There are two main perspectives for evaluating which auction performs 'best'. The first is the perspective of the auctioneer, measured in expected revenue. Second is the efficiency of the overall system in allocating the object to the bidder that values the object the most. Krishna [115] presented an overview of these auctions as well as a comparison of different criteria, for example its resistance against collusion between bidders. There is also research available on the best strategies of bidders in different types of auctions [116, 117].

Many other types of auctions exist, for example hybrids of classical auction types or combinatorial auctions, which cover the sales of multiple units in one auction. Zheng and Koenig [96] considered three types of auctions currently in place for task allocation specifically:

- SSI auctions: Tasks are assigned in rounds to an agent with the lowest team cost [118].
- Auctions with Regret Clearing: The task with largest regret is assigned to an agent with the largest increase in team cost [119].
- Sequential Bundle-Bid Auctions: Two tasks are assigned to agents in order to increase the team cost the least [120].

4.1.3. Bargaining

Bargaining is defined by the Cambridge Dictionary as ”discussions between people in order to reach agreement on something such as prices, wages, working conditions, etc.”. Winoto et al. [117] mention that bargaining can be beneficial over auctions when, for example, feedback from negotiators is important, or social factors such as trust and friendship play a role. Besides, auctions generally need multiple bidders to perform well, while sometimes an auctioneer does not have the time to wait for multiple bidders to join the process. Bargaining is alternatively also referred to as the alternating-offer-protocol.

The first one-to-one alternating-offer-protocol was analyzed by Stahl [121] and later Rubinstein [122]. Rubinstein’s model is mostly studied for game theory as well as multi-agent system theory [123]. The idea is quite straightforward: agents make offers in multiple rounds, and the other agent can reject or accept this offer. When the offer is rejected, the agent can, on its turn, make a counteroffer. This continues until an agreement is reached. While auctions require one-to-many negotiations (in some cases also one-to-one) and contract net protocol focuses on many-to-many negotiations, bargaining is used both for one-to-one negotiations as well as many-to-many. Many-to-many bargaining requires the formation of teams of agents that aim for a joint payoff (which they can distribute among themselves if favoured). In the many-to-many bargaining protocol, proposed by Osborne and Rubinstein [124], players can make offers and all others need to agree. Thus every agent has a veto-right to reject a proposal.

Time is extremely important in bargaining, also referred to as the impatience of agents [20]. Since negotiation cannot go on forever, it makes sense to pose a deadline on bargaining. Sandholm and Vulkan [125] developed a model for one-to-one bargaining of agents with deadlines. It was observed that agents waited with sending out offers until the deadline is reached. Murnighan et al. [126] also observed this phenomenon in human experiments. The optimal agent for bargaining under deadlines would be to wait until the deadline or the other agent accepts. Sandholm and Vulkan [125] propose giving agents time discount functions instead of deadlines in agent models to account for this phenomenon.

Winoto et al. [117] considers two categories of bargaining theory: strategic bargaining and axiomatic bargaining. Axiomatic bargaining, introduced by Nash [127], is based on the concept of axioms that are set initially and will define the solution later. Common axioms are: the egalitarian solution (splitting surplus among all bargainers), the utilitarian solution (maximum sum of participants utility), the Nash solution (noncooperative payoff for each player as well as a share of the payoff from cooperation) [127] and the Kalay-Smorodinsky solution (maintains the ratios of maximal gains) [128].

4.1.4. Voting

Winoto et al. [117] refer to voting as ”a social choice mechanism in selecting social preferences over a set of alternatives”. This mechanism is generally considered to be not as effective as the other negotiation techniques, because the agent that needs the task most will not have a higher chance in obtaining the task. Furthermore, communication costs are relatively high [117]. However, since voting was performed for decision making on task allocation in one of the hangars at KLM Engineering and Maintenance, it could be of interest for this research.

Voting is part of a more formal theory called social choice theory. In social choice theory preferences are usually assumed as a linear ordering over the set of possible outcomes [20]. A social welfare function is used to display the overall preferences of individuals. A social choice function, however, produces a single output, namely the most preferred option by the individual preferences of the voters. Marquis de Condorcet (1743-1794) showed one of the difficulties with respect to voting, by showing that there are scenarios that no matter which option is chosen, the majority of voters will be unhappy with that outcome and can point out another candidate that they would all prefer [20]. Arrow and Debreu [129] showed mathematically that there can be no reasonable social choice function. Several properties of a social welfare function are proposed by Campbell and Kelly [130]:

- *Pareto condition*: If every voter ranks A over B, than A is preferred over B.
- *Condorcet winner condition*: The majority prefers the outcome over all other outcomes.
- *Independence of irrelevant alternatives*: The social raking of A and B should depend only on the way that A and B are ranked in the preference orders, and not on some other option C.
- *No Dictatorship*: The social welfare function should never display one voters' preferences, irrelevant of the preferences of other voters.

Many research has been focussing on strategic behaviour among voters [20]. Conitzer and Sandholm [131] added an extra preround to an existing voting protocol to discourage manipulation of voters by making it computational hard. Another way to deal with strategic voting is to apply a Clarke mechanism, where agents need to pay an initial price in order to be able to vote [132]. Lev and Rosenschein [133] evaluated an iterative voting process where agents were allowed to change their votes, one by one, after the initial voting rounds. Meir et al. [134] proved that, assuming all voters have equal weight and vote according to their preferences, this process of iterative voting, using the plurality voting rule converges to a Nash equilibrium.

Other research into voting mechanisms was for example performed by Pitt et al. [135], that introduced institutional powers into a voting model. Conitzer [136] compared voting mechanisms with combinatorial auctions in terms of outcomes. Conitzer [137] evaluated whether a social network should be taken into account during elections. Nitzan and Paroush [138] showed that more skilled people should have a larger weight, since they are more likely to be right. Better connected people are more likely to be right, but should, in contrast to better skilled people, not receive a more weight in voting protocols [137].

4.2. Modeling Negotiation Processes

The negotiation process can be modeled in four phases: the information phase, intention phase, agreement phase and the settlement phase [20]. The first, information phase, requires agents to communicate and receive information on the negotiation. Then, agents will define their strategies in the intention phase. During the agreement phase, the negotiations will take place and finally in the settlement phase, the final decision is agreed upon. The next subsections will cover these different phases of a negotiation process in more depth.

4.2.1. Information - Resource Valuation

Resource valuation is generally based on economic theory. In this literature research the main theories present in economics will briefly be described, whereas afterwards an example will be presented on utility theory for resource valuation within agent-based modeling.

Economic Theories

There are many economic theories on the valuation of goods in economic research. It is important to note that in general, the usefulness of a resource is referred to as 'use-value', while 'exchange-value' is the resource's proportion at which it is exchanged with other resources [139]. So, price could be seen as a type of exchange value: as the ratio at which a resource exchanges with money.

There are two main streams of theories of value, namely intrinsic (also objective) and subjective theory of value. Intrinsic value theory assumes the existence of an objective value, which is not related to what people are willing to pay, but what the resource is really worth [140]. Many intrinsic value theories exist. For example, Karl Marx defined the Labor Theory of Value, where a good or service is defined by the labor required to produce it [141]. Another is the Exchange Theory of Value [142], which focuses on the use-value of resources, where the need of a resource as well as the physical needs (and labor) create together the intrinsic value of a resource. Other intrinsic theories are more recently developed ones, such as the Monetary Theory of Value [143] and the Power Theory of Value [144].

Subjective theory of value, however, assumes that people have their own idea of determining the value of a resource, which is based on their marginal utility: the additional satisfaction of an additional resource [145]. In this theory the availability of a resource is a key aspect, while this is not considered in intrinsic value theories [145]. Subjective theory of value introduces the concept of an individual's utility, which is a function of the person's preferences over a set of choices. Utility functions can be expressed in two different ways, namely:

- Cardinal, which assumes that utility differences can be measured quantitatively [146].
- Ordinal, which assumes that ordering of preferences based on utility differences is possible, but not the strength of these preferences [129].

The question is how these preferences could be retrieved from real-life applications. Revealed preference theory assumes that by analyzing purchasing habits, the preferences of buyers can be 'revealed' [147]. Similarly, for resources that are not buy-able, a method called Contingent Valuation (also refetred to as "stated preference" in literature) is frequently used, and uses surveys to ask people how they value certain resources [148].

A not all-encompassing, but interesting theory that should to be mentioned is Kahneman and Tversky's Prospect Theory [149]. The key finding of this research is as follows: people are risk averse for gains and risk seeking for losses of high probability, while for a low probability, humans appear to be risk seeking for gains and risk averse for losses. They conclude that people base their valuation of resources based on gains and losses, instead of the final objective outcome.

Examples of Resource Valuation Modeling
Information about characteristics of negotiation, such as a deadline or utility functions can be assumed to be perfect as well as imperfect in multi-agent systems [150]. In case of perfect information negotiations, an agent is assumed to know all this information, while imperfect information considers uncertainty. A model for uncertain utility functions is presented by Goeree and Offerman [151] and Fatima [150]. Similarly, Fatima et al. [20] also outlines an analysis for discount factors. A discount factor considers the importance of time for valuations.

Goeree and Offerman [151] modeled a single-object resource valuation for both common and private values, with incomplete information. The common value (V) of the object to the number of bidders (n) is equal, but the bidders do not know this value in the beginning. Every bidder bases its valuation on its available information, which is modeled as an estimate (v_i) of the object's true value V from a probability density function $A(v)$ with support $[v_L, V_H]$. The true value, however, is the same for all bidders and is modelled as the average of the bidder's estimates, as illustrated in Equation 4.1.

$$V_1 = \frac{1}{n}\sum_{i=1}^{n} v_{i1} \tag{4.1}$$

A participant's private value is modelled as its cost, c_i, which is drawn from a distribution function G(c) and is independently distributed from the value estimates. If participant i wins and pays b, then the utility it gets is V_1 - c_i - b. A summary statistic, surplus, is used to determine bid (b) based on v_i and c_i, which is equal to Equation 4.2. Fatima [150] considers an extended version of this model, including multiple resources to be negotiated in a sequential order.

$$S_i = \frac{v_i}{n} - c_i \tag{4.2}$$

4.2.2. Intention - Decision Theory

Parmigiani [152] refers to the goal of decision theory as "the study of logics and mathematical properties of decision making under uncertain conditions". An important division in theoretical decision theory that should be mentioned is the difference between normative and descriptive models. While normative models describe how an agent ’should’ behave, a descriptive model describes how an agent ’really’ behaves [149]. With respect to decision-making models, three types of strategy modeling for agents were distinguished by Kraus [48] and Wooldridge [54]: game-theoretic strategies, heuristic strategies and argumentation-based strategies. The following sections will provide more information on these three techniques.

Game-Theoretic Approaches
Game Theory is defined by Myerson [153] as ”the study of mathematical models of conflict and co-operation between intelligent rational decision-makers”. The general question in game theory is, what specific option any rational agent, when presented with a scenario of alternatives, will choose regardless of what an other agent does [21]. There are two main ways of representing a game: normal-form (using a matrix with options) or extensive-form (using a game tree) [146]. A normal-form game requires complete, perfect information, while extensive-form games allow for incomplete information and sequencing of decisions [21]. Zhang et al. [99] considers four main characteristics of game theory methods: its players, the use of payoff functions, strategies and the order of decision-making. These characteristics will be elaborated on below.

Players - One can distinguish in cooperative and non-cooperative game theory [21]. The essential difference between the two branches is that in non-cooperative game theory the basic modeling unit is the individual (including his beliefs, preferences, and possible actions), while in cooperative game theory the basic modeling unit is the group [21].

Payoff Functions - Utility theory is often used to quantify preferences across a set of available alternatives [21]. Sometimes the expected value of an utility function is taken from a probability distribution utility function [21]. However, the assumption that agents would base their decisions on the expected value of their outcomes is unjustified. That is why a preference-based method was introduced by von Neumann and Morgenstern [146]. This theory makes use of ordering outcomes, in which an agent is able to express its preference of one alternative over the other.

Strategies - Agents’ strategies in game-theory represent their available choices [99]. There are two distinct strategy profiles: a pure strategy profile and a mixed strategy profile. A pure strategy results from the choice of one action over other actions. A mixed strategy makes use of a randomization of the choice for an action based on a probability distribution [21]. Some games have dominant strategies, where a rational player has no incentive to choose another strategy than the dominant strategy.

Ordering Strategies - When analyzing individual strategies, many different concepts could be applied. A sole agent can have an optimum strategy, that say, is the best strategy for maximizing the agent’s utility. However, for multi-agent environments, there are several solution concepts to consider for analysis of the system [21]. A Pareto dominant strategy means that an agent can increase its utility without decreasing another agent’s utility. Strategy ’S’ is a Pareto optimal strategy, if there is no other strategy that Pareto dominates that strategy ’S’. A strategy profile is a Nash equilibrium, if for all agents i, a strategy A is the best response (the highest utility gain) to every strategy by another agent.

Criticism - A general criticism on decision theories making use of a finite amount of possibilities, is that only the ”known unknowns” and not the ”unknown unknowns” are considered. This is also referred to ”ludic fallacy” in literature [154]. One of the most discussed disadvantages of game theoretic approaches in particular is that it assumes all players to be completely rational [99, 117]. However, real people are assumed to be bounded rational. Section 4.3.1 explains more about bounded rationality in human decision making. Some researchers have been trying to incorporate aspects of bounded rationality in game-theoretic approaches, such as only providing local information [155], considering players’ personal traits [156], using machine learning techniques for agents’ reasoning power or setting computational limits for alternative generation [157]. However, Cimini and Sanchez [156] argue that statistics from experimental research to back up bounded rationality elements, and to be able to assign significant values to players, remains insufficient for game theoretic approaches. More research is required in order to develop a game that accurately considers human bounded rationality. The issue with game theory is that it aims for finding optimal solutions, but without this information, these 'optimal' solutions will not hold for bounded rational models. This is where heuristics or argumentation-based approaches come into play.

Heuristic Approaches
Another approach of modeling decision-making involves heuristic strategies. Heuristics are defined by social scientist Myers [158] as a mental shortcut that eases the cognitive load of making a decision. Jennings et al. [154] state that the goal of using heuristic methods in multi-agent systems is to overcome limitations of game-theoretic models, since heuristic methods acknowledge that computation and decision-making are costly and explicitely considers agent bounded rationality [20]. Heuristic methods are not about producing optimal solutions, but solutions that are good (enough). Fatima et al. [20] outline the three main heuristic negotiation research areas: the generation of counter offers, the prediction of other agents' strategies and finding and setting optimal negotiation agendas. Since setting of the agendas does not relate directly to the current task allocation problem in aircraft maintenance, only the first two research areas will be elaborated on.

Generating Counter Offers - Faratin et al. [159] defined three types of strategies for counter-offer generation using heuristics: time-dependent strategies, resource-dependent strategies and behaviour-dependent strategies. Time dependent-strategies focus on the eagerness of agents to compromise as deadlines approach. Resource dependent strategies reflect the available resources in the environment. Behaviour-dependent strategies incorporate all other approaches when there is no pressure in terms of time or resources and offers are based on previous attitudes. Since in task allocation for aircraft maintenance both time as well as resources could be of importance, behaviour-dependent strategies will not be considered further. The mathematical representation of the time and resource dependent strategies are similar, since time could be seen as a limited available resource. A time dependent negotiation strategy is modeled by Faratin et al. [159] as follows: Let j ∈ {1,2...,m} be an issue, with a certain price, to be negotiated. The price offered by agent A at time t is calculated according to:

$$x^j_{a\to b}(t) = \begin{cases} min^a_j + \alpha^a_j(t)(max^a_j - min^a_j) & \text{if A's utility decreases with price} \\ min^a_j + (1-\alpha^a_j(t))(max^a_j - min^a_j) & \text{if A's utility increases with price} \end{cases}$$

At t=0 the offer will be in a point between min^a_j and max^a_j and when the deadline t_max^a is reached, the offer will be the reserve price max^a_j. The definition function $\alpha^a_j(t)$ could have different shapes (as a function of time), such as a polynomial function using a parameter β (β being real and positive):

$$\alpha^a_j(t) = \kappa^a_j + (1-\kappa^a_j)(min(t, t^a_{max})/t^a_{max})^{\frac{1}{\beta}}$$

In this case, for a small β, the initial offer is maintained until close to the deadline and then a fast compromise is made. While for a large β, the reserve value will be offered much earlier. A similar model could be applied to resource-dependent strategies, only making the value of t^a_{max} dynamic for the scarcity of the resource or making the function α dependent on an estimation of the resources that are still available [20].

Strategy Prediction - Many approaches for predicting opponents' strategies have been developed over the years, by Genetic Algorithms [160], Bayesian learning frameworks [161], or fuzzy approaches [159, 162]. An overview of strategy prediction using heuristics can be found in Fatima et al. [20].

Criticism - Jennings et al. [154] considers the fact that models are based on realistic assumptions as an advantage of heuristic models, since they can be applied in a wide range of domains. Besides, using alternative models than game theory can provide other insights in multi-agent systems. However, heuristic outcomes are sub-optimal, since not all possibilities are explored. Secondly, heuristic models need extensive evaluation for verification and validation purposes, because it is impossible to predict how the system will behave under certain circumstances [109].

Argumentation-Based Approaches
In argumentation-based approaches, arguments are exchanged between agents influencing each others' states [109]. This allows agents to explicitly communicate their opinions about a proposal. The

arguments presented by the agents are not necessarily true. An agent can modify its opinion to an argument, such that it will be convincing for the other agent [92]. Within game-theory and heuristic methods, the utilities of agents are assumed to be fixed, while the focus of argumentation-based approaches is on the evolution of beliefs about preferences. Therefore, an argument can be used to justify a proposal, or to influence another agents opinions [163].

Rahwan et al. [109] provided an extensive overview of the elements argumentation-based negotiation should contain and the frameworks that have been proposed until then. Generally, compared to game-theoretic or heuristic approaches, more elaborate interaction protocols, negotiation protocols and communication languages are necessary to accommodate for the additional information exchange in argumentation-based negotiation models. Most argumentation-based agents contain a knowledge base of their mental attitudes as well as the environment [109]. This knowledge is then used to evaluate and generate proposals. Arguments can be used to update this knowledge base. Moreover, the knowledge base can help to generate candidate outgoing arguments as well as select one of the available arguments. Rahwan et al. [109] argued that the evaluation, generation and selection of arguments are the main phases of argumentation-based negotiation. These will be elaborated on below.

Argument Evaluation - Argument considerations can be divided between objective and subjective considerations. In the first case, an agent can evaluate an argument according to some standard mechanism. Elvang-Goransson et al. [164] based this on the strength of the construction of the argument, and Dung [165] defined an argument to be acceptable if every other argument that attacks it, is attacked by yet another argument. Besides, an agent can also consider its own preferences and motivations in evaluating arguments, which leads to subjective considerations. For example, Bench-Capon et al. [166] included the preferences of values for different agents in their evaluation protocol. Rahwan et al. [109] argues that in order to satisfy agents' individual as well as common goals, both objective as well as subjective argument evaluation is necessary.

Argument Generation - Generally, proposals are generated based on agents' utility gain [167] or a central planner agent is used to generate options [48]. Argument generation can incorporate many influences, such as authority or honesty elements [109]. An example of argument generation was presented by Kraus [48], which provided an informal approach to model a threat argument [109].

Argument Selection - Finally, an agent should select the most suitable argument for the corresponding negotiation partner. Rahwan et al. [109] stress that it is not needed to generate all possible arguments, but the generation process can stop when a suitable argument has been found. An example criteria for argument selection is the level of trust of an agent related to the strength of an argument [168]. One could wonder why agents would ever send a weak argument. However, when a strong argument is presented, the chances of decreasing trust of the opponent are higher, which will make it harder for the agent to have the opponent accept future proposals [109]. Many other selection criteria have been presented, such as the availability of a counter example [48], the promise of future reward [48], the costs of alternative plans [169] and preferential ordering of alternatives (such as the argumentation evaluation by Amgoud and Prade [92] or Dung [165]).

Criticism - Next to the advantages explained in the beginning of this section, argumentation-based negotiation also has the advantage that it allows for rather straightforward explanation of the decision that has been made [86]. A problem however is that communication overhead will become very large [92]. Besides, the technique is relatively new and therefore not many frameworks or implementations are present [109]. Moreover, the social aspects of argumentation in groups of agents are key in establishing solid argumentation-based negotiation frameworks, with trust being an essential social factor. However, formal theories of these social elements are scarce.

4.2.3. Agreement and Settlement

The solution of negotiations can be evaluated on many aspects. Specific game-theoric concepts have already been elaborated on in Section 4.2.2. A share of other negotiation performance indicators are:

- *Pareto efficiency*: No option will make someone better off without making another worse off [21].

- *Guaranteed payoff*: If a player has an expected payoff of at least a certain value [21].
- *Guaranteed welfare*: If the sum of each players' utilities is at least a certain value [21].
- *Maximum Social Welfare*: If the outcome of the utilities is the best for the entire system, most generally modeled using a welfare function [153].

4.3. Negotiation with People

The goal of socio-technical modeling is to uncover relations between technologies and human societies. That is why this section will be focused on the relation of automated negotiation with people. According to Fatima et al. [20], game-theory is not applicable for accurate analysis and simulation of negotiations with people, because of its rationality assumption. Kahneman et al. [170] provided a list with experimental evidence against the Bayesian rationality in human decision-making processes. The notion of bounded rationality focuses on the 'deviations' of human-decision making on pure rational decision-making processes.

4.3.1. Bounded Rationality

The idea of bounded rationality was first introduced and defined by Simon [171]. Bounded rationality assumes that rationality of humans is limited by the available information, human cognitive abilities and the finite amount of time for making a decision [171]. Gimpel et al. [172] performed a literature survey on cognitive biases in negotiation, of which a summary is provided below:

Offer analysis

- *Framing*: A choice can be framed positively or negatively.
- *Fairness*: People have their own idea of fairness, which is subjective.
- *Fixed pie illusion*: People frequently focus on specific issues, instead of looking at all available alternatives and finding a compromise.

Beliefs

- *Probability weighting*: According to prospect theory, people overestimate low probabilities and underestimate high probabilities [149].
- *Availability*: People can be mislead by a probability of some consequence by an easy available experience in their memory.
- *Overconfidence*: People tend to overestimate their abilities and correctness.

Preferences

- *Reference points*: People evaluate an outcome as gain or loss with respect to a reference point [149].
- *Attachment*: People can be attached to expectations on the outcome of the negotiation process.

Strategies

- *Ignorance of others' behaviour*: People do not always take into account the strategies of others, while that is assumed in game theoretic approaches.

Offer specification

- *Anchor and adjust*: People tend to start with a certain value with available information at that moment and adjust it according to new available information, instead of evaluating the issue again from the start with this new information.

Internal states

- *Escalation of conflict*: Sometimes people rather avoid a loss than postponing the decision.
- *Memory*: People tend to selectively store information, or forget certain information over time.

A limitation of this psychological perspective is that it lacks mathematical formalization. However, the descriptive validity of these biases could be useful.

4.3.2. Automation in Human Negotiation

Automated negotiating agents can be beneficial for humans in two ways [20]. Firstly, automation of negotiations can relieve some of the effort from people [4] or even replace humans [173]. Secondly, these agents can assist humans in their decision making in the negotiation process [108] or be used as a training tool [174], in order to improve human negotiation abilities. The latter is also referred to as Negotiation Support Systems [175]. The next subsection will focus on the use of support systems in negotiation, followed by a more thorough analysis of the use of automated negotiation agents and their interaction with humans.

Support Systems in Human Negotiation Processes

Several variations on Decision Support Systems have been developed for negotiation purposes. Kersten and Lai [4] consider different types: Negotiation Support Systems (NSS), E-Negotion Systems (ENS), Negotiation Software Agents (NSA) and Negotiation Agents-Assistants (NAA). A negotiation support system is "software that implements models and procedures, has communication and coordination facilities and is designed to support two or more parties and/or a third party in their negotiation activities." An e-negotiation system however focuses on internet technologies for facilitating on negotiation. The difference between a NSA and a NAA is that a Negotiation Software Agent actively makes decisions on behalf of a person, while a Negotiation Agents-Assistant only provides support [4].

Kersten and Lai [4] also presented the difference between negotiations in social and socio-technicial systems. While in a social system software could be used as a tool (such as email), in a socio-technical system negotiators rely on software that actively engages in the negotiation process. A schematic overview of how these different types of support systems could be used in a social versus a socio-technical system can be found in Figure 4.2. A directional arrow indicates the usage of tools by people, while an arrow in two directions shows communication between these systems.

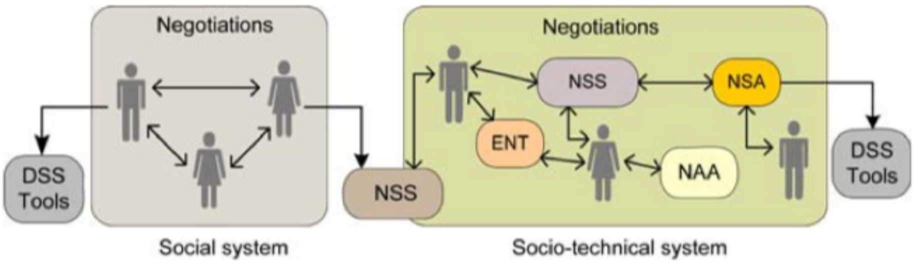


Figure 4.2: Negotiations in social and socio-technical systems [4]

The review paper by Kersten and Lai [4] stresses the role of a neutral third party that computer systems could take. This could be in a facilitating role (allowing communication and coordination), a supporting role (assist in cognitive aspects of negotiation) and a mediating role (actively shape the process to find an agreement). The facilitating role is a physical support system, while the other two are extending human mental capabilities. Several configurations of negotiation software and their implications are presented in this review and could be useful when designing an architecture for supporting software. An overview of these configurations can be found in Figure 4.3.

One of the key challenges of Negotiation Support Systems is a lack of theoretical foundation [176]. Kersten and Lai [4] argue that a more systematic approach to designing instruments and experiments is required. This includes the impact on people's cognition, but also attitude and the interactions between negotiators [176]. Research has therefore been performed on the social acceptance of NSS for example, by Pommeranz et al. [177]. Another study by the same research group focused on the emotional state of negotiators and how to incorporate affection in these systems [175].

Although the time to achieve an agreement is higher using NSS, it has been shown that they reached higher joint outcomes as well as more balanced individual outcomes than negotiations without these systems [178, 179]. In negotiation with automated agents, humans appeared to be performing slightly better [179]. An explanation given for this phenomenon is that humans forced the agents to compromise and agents therefore need to be designed to resist human manipulation.

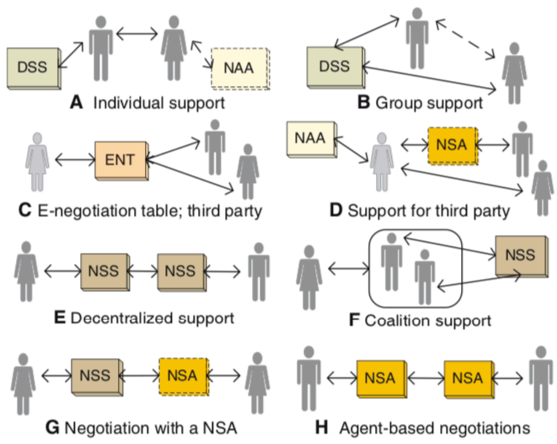


Figure 4.3: Configuration of negotiation software [4]

Automated Negotiating Agents in Human Negotiation Processes
Fatima et al. [20] classify the existing automated negotiation agents in two categories: rule-based agents and utility-based agents. The first makes use of rules for decision-making that are set by experts, based on for example human-to-human negotiation situations [180] or negotiation over payments for tasks in crowd-sourcing domains [181, 182]. Haim et al. [183] created a rule-based agent using machine learning techniques without the need of expert knowledge for rule development.

A key aspect of automated negotiating agents with humans is that the agents need to be able to predict human decisions. An approach to this is modeling personality traits of its negotiation partners. The DIPLOMAT agent, developed by Kraus and Lehmann [184], was the first to make use of personality mapping. Another approach was to model participants on two personality characteristics: reliability and helpfulness [20]. Santos et al. [185] used a concept from psychology, the Five Factor Model of personality traits (FFM), which stands for Openness, Conscientiousness, Extraversion, Agreeableness and Negative emotionality [186]. This model has not been validated in experiments with people, though.

Another approach in predicting decisions is making use of subjective expected utility Fatima et al. [20]. Subjective expected utility assumes that each person has its own subjective evaluation of alternatives, given certain actions and inputs from the environment [187]. However, Simon [171] argues that this subjective expected utility theory (in psychology) does not fit empirical findings in human decision-making. Selten [188] also argues that it does not lead to a realistic description of bounded rational decision-making. Rosenfeld and Kraus [189] used the aspiration adaptation theory to improve prediction on how people negotiate. The aspiration adaptation theory uses human satisfaction as a core instead of optimization [188].

A social utility function could also be used to model social preferences, which reflects the fact that people take the preferences of their opponents in consideration when making a decision. Gal and Pfeffer [190] proposed a model of several social factors together with individual utility and developed an algorithm for determining these factors from data of people’s negotiation performance. Other approaches include the use of reinforcement learning on the behaviour of opponents [191] as well as the use of visual expressions in automated negotiation [192].

5
Social Simulation

An essential part of this literature research is the understanding of social aspects in task allocation. While in most research, only the technical implications of these systems are evaluated (see Chapter 4), the focus of this chapter is to consider the functioning of the task allocation system as a whole: not only the technology, but also the social context in which it operates. This chapter will first provide some information on social structures in organizations, as well as existing methods for modeling these social structures. Subsequently, the social factors that are believed to be relevant for task allocation in aircraft maintenance are presented and elaborated on.

5.1. Social Structures

Social structures represent interactions and patterns in social systems. The term was firstly used by Alexis de Tocqueville and consequently used by Karl Marx and Max Weber. Crothers [193] provides an overview of the many different definitions available in sociological research. After an extensive evaluation of the existing definitions, Crothers [193] therefore states that social structures "are at least somewhat-enduring sets of relationships among a group of roles which emerge, are maintained, change and eventually cease." Many classifications on social structures exist, but most sociologist seem to agree that there is at least a distinction to be made between, firstly, the study of relationships between individuals or groups of people, and secondly, behavioural (or normative) patterns by individuals in a social system that emerge over time [193].

Sociologist Max Weber described an organization as a "social relationship which is either closed or limits the admission of outsiders, when its regulations are enforced by specific individuals: a chief and possibly, an administrative staff, which normally also has representative powers" [194]. Organization theory research started with engineers trying to standardize not only units and bolts, but also the way organizations are set-up and organize themselves [195]. Soon, researchers from psychology, anthropology, economy, management and sociology joined to provide another view on how organizations are, and should, be organized [195].

The research of social psychologists within this field provided more insights into individual motives and anthropologists and sociologists showed unofficial, informal patterns of cooperation, shared norms and conflicts between and among managers and workers [195]. Many sociologists emphasize the dualist nature of organizations: on one hand organizations can be viewed as production systems, but on the other hand as adaptive social systems [196, 197]. Helbing [198] argues that it is inefficient (and sometimes impossible) to try and rule over self-organization within complex systems. That is why social structures and social self-organization within the organizational context of this research are key.

5.2. Modeling and Simulation of Social Structures

Modeling social structures is however still a relatively unexplored research area. That is why some recommendations on modeling social processes in general could be helpful for this research. Firstly, Epstein [199] argues that the purpose of the model should be clearly defined. This could for example be the prediction of social processes, explanation of these processes or the training or education of people involved. Jonker and Treur [200] argue that, next to a purpose, a design rationale is key. This design rationale is the guiding theme for model development and is able to explain most (if not all) design decisions that have been made. In Jonker and Treur [200] a formal approach for designing agent-based models in organizations is presented.

A common misunderstanding in the simulation of human processes is that the model should include all the human cognitive aspects that could be distinguished. However, in most cases, a much simpler model serves the modeling goals better [200]. Besides, as Sharpanskykh [66] argues, when a large number of variables and functions is used to model complex organizations, the models' complexity increases enormously and controlling the model gets hard. As Mercuur et al. [201] puts it: ”social simulation gains strength when agent behaviour can represent human behaviour and be explained in understandable terms”.

5.2.1. Emergence

A key concept in social simulation (and social sciences in general) is emergence, which concerns the relation between system-level properties and the properties of the system components individually [202]. Two perspectives on emergence are distinguished in literature [202]: the ontological view and the epistemological view. The ontological view assumes that the overall (global) result, is more than the sum of all the individual results. In contrast, the epistemological view assumes that the total system is nothing more than the sum of these parts, but that it is simply to hard to explain or quantify all the different parts precisely [202].

Usually emergence serves as an outcome of a simulation model, based on individuals, with beliefs, intentions and relations with others. Yet sometimes these types of models can be too limiting in representing higher level system properties. In these cases, Sawyer [202] argues that macro concepts could also be incorporated in the design of these models, next to the individual agent properties, with inter-agent connections between these two entities as relations between the two system levels.

5.2.2. Social Simulation Drawbacks

In literature several drawbacks of social simulation could be differentiated. In this section a brief a summary of these issues is presented:

- A challenge for social simulation is the lack of formal models for many social concepts. This makes it difficult to verify models and accurately represent social processes [203].
- Social simulation is on the edge of computer science, mathematics and social science. Since social scientists generally do not have any experience with or knowledge of mathematics or computer science, social scientists generally make use of informal models for social simulation. These informal models make it easier to rush into conclusions and lack validity [203].
- When social simulation has been successful, overconfidence in explanations of real-world processes could be risky. Sawyer [202] argues that, even when the model fits empirical validity, the explanation might not be complete.
- Sawyer [202] also states that the meaning and implications of social simulation results can be difficult to communicate to non-technical social scientists.
- A key aspect of social simulation, and more specifically agent-based social simulation, is incorporating diversity within the system. Barreteau et al. [204] argues that this does not only relate to individual beliefs, but also viewpoints, expectations of the system and decision-making. Involving stakeholders in the modeling process could be a way of introducing different viewpoints and expectations to the modeling process.

5.3. Social Factors

In this section an overview of the social factors that could be of interest for this research is presented. These factors were established by accurately studying the task allocation process currently in place and evaluating possible factors that could be playing a role. These social factors also influence each other and overlap in some instances. These aspects are categorized into individual properties, social interactions and interactions with the environment.

5.3.1. Individual Properties

This section elaborates on some general properties that are of interest for human decision-making in general, but more specifically for task allocation in aircraft maintenance. The factors considered are: human goals, values, motivation and skills.

Goals

A goal is defined by the Oxford Dictionary as an 'objective of an individual's ambition or effort'. In social psychology, a distinction is made between implicit and explicit goals. Implicit goals refer to the non-conscious goals that people pursue, while explicit goals are set consciously by people themselves (or others) [205]. People switch between goals regularly [206].

This temporal aspect of goals is also considered in Sharpanskykh [66]. The author outlines the importance of making the distinction between the overall goals of an organization and the individual goals of the actors that perform tasks in this organization. These goals can be conflicting or not completely aligned. Based on the self-determination theory [66, 207], three different types of needs are distinguished that drive individual goals:

- *Extrinsic needs:* An individual's biological comfort and material rewards.
- *Social interaction needs:* Social approval, affiliation and companionship.
- *Intrinsic needs:* Self-development, self-actualization, mastery and challenge.

A well-known example of modeling agent goals and values is the concept of BDI-agents (belief-desire-intention agents) [208]. For more information on the BDI agent architecture, see Section 3.2.2.

Values

In contrast to the changing nature of goals, values are lasting convictions that people feel that should be aimed for in general [209]. Values can be intrinsic, a purpose in itself, or instrumental, a means to reach an intrinsic value [209]. Generally people have multiple values driving their actions. But, Miles [210] stressed that these connections are rather weak. A choice between options with multiple relevant values gives rise to a value conflict, specifically when no option is obviously the best one [209].

Several possibilities for dealing with these conflicts exist for human decision-making [209]. The first is a cost-benefit analysis, where the advantages and disadvantages are expressed in some number and the overall cost or benefit of each alternative is calculated. This method, however, has the underlying assumption that values can be expressed in terms of some utility number (or money). Another method is a multiple criteria analysis, where each alternative is scored on several values and an overall score is calculated. This method also assumes that values can be traded-off. However, it does not assume explicitly that all values can be converted to the same utility unit. Furthermore, thresholds can be used to compare values. In that case, a minimum required level is set for all values separately. Finally, a non-calculative approach is the judgment of and reasoning about values. In this approach three steps are identified: find the relevant values, specify these values and then look for common ground in these values. This method is more a philosophical approach than a simple solution to value trade-offs [209].

Mercuur et al. [201] represented an agent in terms of its values using the ten basic values defined by Schwartz et al. [211]. In this model Mercuur et al. [201], only modeled the values wealth and fairness of agents, which are negatively correlated and allowed for quite straightforward decision-making. It is therefore questionable how this model would be operating if more (and less correlated) values would be considered. Furthermore, human dynamics in multi-round decision-making cannot be reproduced based on values, since values stay the same over time.

Motivation

Although many definitions for motivation hold, it all comes down to the degree to which an individual is 'moved' to do something [212]. Similar to goals, motivations can also be intrinsic or extrinsic [213]. Intrinsic motivation refers to the motivated behaviour that follows interests for the inherent satisfactions, while extrinsic motivation follows some consequence or outcome of the action [213].

An example of an agent-based model using one of the motivation theories from social science, is Sharpanskykh [66]'s model for the motivation of agents using Vroom's expectancy theory. This theory makes estimations for three factors: expectancy (likelihood of some first-level outcome), instrumentality (likelihood of some second-level outcome) and valence (strength of a desire for an outcome). The motivational force for act F_i and valence V_j can then be calculated as follows:

$$F_i = f(\sum_{j=1}^{n} E_{ij} \cdot V_j) \qquad\qquad V_j = \sum_{k=1}^{m} V_{jk} \cdot I_{jk}$$

With E_{ij} being the expectancy of act i followed by outcome j, V_j the valence of first-level outcome j, V_{jk} the valence of second-level outcome k that follows j, I_{jk} the instrumentality of outcome j for outcome k.

Other motivation theories combine expectancy with values instead of direct outcomes. A similar model has been presented by Sharpanskykh and Haest [214], where employee compliance at an aircraft ground service organization was studied based on a model of the employees' motivation. Eccles and Wigfield [215] argued that most motivation theories implicitly assume rational behaviour, but there is a need to also consider affection when studying motivation. A theory that includes affect is the attribution theory, which holds the fundamental point of view that individual's interpretations of outcomes are driving motivation rather than actual outcomes [216]. Besides, the environment is key for motivation and should therefore not be left out [215].

Skills

In Chapter 2 the different types and levels of skills among mechanics were discussed. This mostly relates to the mechanics' technical skills for executing tasks. However, also interpersonal, managerial and problem-solving skills are important within organizations [217]. So, in aircraft maintenance teams skills as leadership, goal-setting, planning and delegation could also be of interest.

The abstraction of skill levels is considered to be a limitation of the models incorporating skills in Chapter 2. This abstraction makes it easier for a central planner to assign tasks, but it does not account for the entire range of capabilities that people possess. The skills and capabilities of different agents are generally more accurately known and acknowledged on the work floor. These skills could therefore be taken into account more accurately in bottom-up, decentralized (agent-based) systems, than in a central task allocation method.

Grow et al. [218] presented an agent-based model in order to uncover the conditions under which hierarchical differentiation between separate groups creates the belief that one of these groups is more skillful than the other, although that is objectively not the case. It was observed that hierarchical differences were most likely to occur in smaller teams that work together for a very short or very long time. This research did not account for an actual existing difference in experience and how that relates to status formation within groups.

5.3.2. Social Interaction

This section elaborates on theories that describe sociality aspects, such as the dynamics of teamwork, social influences, power relations, norms and the diffusion of innovations.

Teaming

Weiss [59] defined a team as "a group in which agents are restricted to having a common goal of some sort. Typically, team members cooperate and assist each other in achieving their common goal". The four stages of team processes that are generally distinguished in literature are [219]:

1. *Potential recognition:* A team lead recognizes potential team members for a potential goal.
2. *Team formation:* The team lead establishes collective intention between team members.
3. *Plan formation:* All team members agree to create collective commitment for realizing the goal.
4. *Team action:* All members will be executing their shares of the tasks.

A lot of research exists in the first two phases [220, 221]. Yet this research focuses mainly on the phases of plan formation and team action, since in aircraft maintenance teams are already established beforehand [222]. Teams distinguish themselves from other social groups by the presence of a team leader that aims at solving a problem for which it needs to recruit team members with the right qualifications for solving that set of problems [223]. Dunin-Keplicz and Verbrugge [224] highlighted five main characteristics of teaming for cooperative problem solving:

- Working together to achieve a common goal. There is no competition among team members with respect to achieving the common goal.
- Constantly monitoring progress of the team efforts as a whole.
- Coordinating individual actions in order to avoid interference.
- Communicating successes and failures if necessary for the team to succeed.
- Helping one another out when needed.

The two latter characteristics have been supported by experimental research, where the problem solving performance of groups outperformed individual problem solving, since the groups profited from complementary knowledge and ideas [225]. This depends also on the communication structure of teams. Unidirectional communication can reduce performance, but on the other hand, communication could also be inefficient if there are too many people in the team communicating [22].

Social simulation research on teamwork within multi-agent systems is, in less amount, also present in literature, for example evaluating reputation [226], diversity [227] and power between and within groups [218, 224]. A way of modeling team dynamics is elaborated on by Dunin-Keplicz and Verbrugge [224]. Three main collective properties were distinguished:

- *Collective beliefs and knowledge:* Agents can have a general belief or knowledge, which means that every agent in the group beliefs or knows 'A' and a common belief, which means that everyone in the team believes or knows that everyone in the team believes or knows 'A'.
- *Joint intentions and goals:* Being aware of and care about the status of group effort as a whole, by creating an individual intention towards that goal.
- *Social commitment:* The individual's commitment towards the social plan, which outlines the responsibilities for every agent, in order to realize the team's goal. The strength of this commitment depends on the situation and the agent.

Poole and DeSanctis [16] state that groups (or teams) share common social practices, such as: making decisions, accomplishing work, socializing, joking, teaching others skills and norms, fighting, establishing power and status relations, meeting individual needs for sympathy, acceptance or self-development. The authors argue that technological support systems should be used to pursue the same social practises that other (social) resources would do.

Social Influence

Social influence lays at the foundation of dynamics in teams as well as interpersonal relations in general [228]. Through social influence people make changes in the social world [229]. Although former research into social influence encompasses the entire spectrum of influences in social context, current research focuses on the subtle, indirect and non-conscious social influences [230].

A general accepted framework for social influence is presented by Cialdini and Trost [230], that encompasses most of the social research into the topic. It is argued that two main behavioral aspects are of interest for social influence: compliance and conformity. Compliance refers to some sort of agreement to a, explicit or implicit, request [230]. Conformity refers to the change in behavior of a person to adjust to the reactions of others. In both cases people adjust their behavior, but compliance does not hold a change in attitude [230]. A person can comply without changing its beliefs for example under obedience, which is social influence based on authority [231], or social pressure [232].

These changes in behavior due to social influences can have many different motivations. Cialdini and Trost [230] argue in a extensive literature review that three main goals for compliance or conformity can be distinguished in literature:

- *Goal of accuracy*: Responding accurately to social situations asks for correct interpretation.
- *Goal of affiliation*: Creating and maintaining sincere social relationships.

- *Goal of a positive self concept*: Behaving consistently with personal beliefs, actions or traits.

Bachrach and Baratz [233] argue that it can be hard to draw the line between power and influence in real-life, since most people are not aware of the power relations that drive their views on certain matters. The next section will provide some more information on power relations, which are generally referred to in cases of more explicit social influences [230].

Power Relations
In social science, power is considered to be of importance for social structures [233]. No comprehensive definition of power exists. One of the influential papers on power is Bachrach and Baratz [233], which argues that a person cannot just 'have' power in itself, but power is always related to someone else. Three conditions are true in the case of (relational) power use: a conflict of interests or values between persons or groups, one person bows to the other persons wishes, and one of the parties can threaten to invoke sanctions [233]. Sibertin-Blanc et al. [234] focus on conflicts over resources, when referring to power as "an instrument for people to obtain means from others to achieve their own objectives".

A widely accepted framework for power relations is proposed by Raven [235]. This framework has been formalized, implemented and simulated in an aircraft maintenance organizational model by Passenier et al. [236]. This model considers six different types of power relations:

- *Reward power:* Based on resources.
- *Punishment power:* Based on the possibility of penalties.
- *Legitimate power:* Based on internalized values of the submissive.
- *Expert power:* Based on knowledge or expertise.
- *Referent power:* Based on relatedness.
- *Informal influence:* Based on persuasion.

Authority considers a normative relationship between two persons, where one person is higher in ranking (within an organization or society) than the other [237]. Sharpanskykh [66] argues that authority has a formal basis, since it involves norms and explicit rules. Sharpanskykh [66] presented a formal model on authority modeling in an electronic enterprise information system, where agents are authorized to execute tasks in an organizational setting.

Reputation also plays a role in power relations. Trust, on its turn is influenced by people's reputation of their skills, intentions or motivation. Besides, trust in (automated) systems driving teams could be important [86]. According to Giardini et al. [238], reputation allows people to predict or approximate what kind of social interaction they can expect from others. Frith and Frith [239] state that one can learn about another by direct experience, observation or cultural information. This latter aspect is not commonly used in agent-based models or social simulation in general.

Norms
Standard, acceptable or permissible behavior in groups can be captured by the concept of norms [240]. Neumann [241] refers to norms as a type of social constraints on the actions of people. An important aspect of norms is that people internalize norms in their decision-making process. Neumann [241] considers three components of norms: an individual component (a belief), a social component (shared beliefs) and a deontic component (an obligation). Similarly, Ostrom and Crawford [242] considered four elements for norms: attributes (individual component), deontic, aim (also an individual component) and condition (social component), which he referred to as the 'ADIC'-elements.

Neumann [241] evaluated the options for the implementation of norms and social constraints for several agent architectures. Influential work in social simulation on norms was performed by Axelrod [243], who modelled a basic game using an evolutionary approach. The establishment of norms was measured using the level of boldness: the chance of being seen when defecting of cooperation, and vengefullness: the probability of punishing someone when observed to be defecting. A norm is established when boldness is low and vengefullness is high.

An overview of agent models taking norms into account is presented in Neumann [241]. It is argued that in literature, three types of norms are implemented: norms as constraints, norms as obligations and norms as abstract concepts. The first are simple rules that are dictated by the designer and restrict the agents freedom, such as in Garcia-Camino et al. [244]. When modeled as obligations, norms are considered mental states that allow for conscious deliberation on norms. Under certain circumstances norms could therefore be violated [169]. Furthermore, norms can be seen as abstract concepts that drive obligations [245]. In this case agents take an outer perspective and evaluate in their decision-making process how others think they 'ought to' behave [246].

Innovation Diffusion
Theory on the diffusion of innovations can be an important social aspect for this research. One of the most influential works on the diffusion of (technological) innovations within social systems has been performed by Rogers [5]. He distinguishes five different phases in this diffusion process:

1. *Knowledge:* Awareness of the innovation.
2. *Persuasion:* Interest in the innovation rises.
3. *Decision:* Evaluate whether to use the innovation or not.
4. *Implementation:* Use of the innovation and evaluation of its use.
5. *Confirmation:* Decide whether to keep using the innovation or not.

Social influences between individuals or groups play a major role in the level of success of this diffusion process [5]. Four variables are believed to be key for this level of success: the innovation itself, how it is communicated, how long the group is exposed to the innovation and the (social) characteristics of this group. Rogers [5] innovation adoption curve among people can be found in Figure 5.1. This curve aims at explaining that people differ in their reaction on new elements being introduced in their lives. It is interesting to see that when around 15% of the people has adopted the innovation, the adoption process speeds up significantly. This can be explained by social influences between people as well as a decrease in uncertainty that attracts risk averse people.

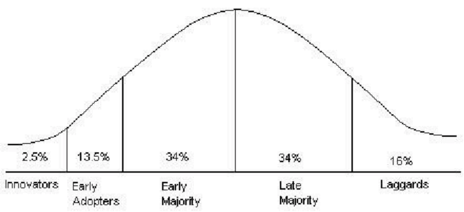


Figure 5.1: Rogers' innovation adaption curve [5]

5.3.3. Interaction with the Environment

Finally, three concepts that are based on agents' view on and interaction with the environment are elaborated on: situation awareness, case-based reasoning and social practice theory. These concepts also relate to social interaction, but are more focused on the agents internal evaluation and decision-making than the concepts described in the previous section.

Situation Awareness
The most common accepted framework and definition regarding situation awareness was developed by Endsley [247]. He refers to situation awareness as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future". This relates to the outcome of gaining awareness, but other researchers also refer to situation awareness as the process of gaining awareness [248]. Endsley [247] emphasizes that situation awareness relates specifically to the dynamic nature of decision-making, the decision-maker's experience and other influences on decision-making, such as stress and attention. Endsley [247]'s framework distinguishes three levels of situation awareness:

- *Level 1*: Perception of status, attributes and dynamics of relevant elements in the environment.
- *Level 2*: Comprehension of the situation through combining Level 1 elements and agent goals.

- *Level 3*: Prediction of future states using the understanding of the current situation.

Endsley and Robertson [249] performed a research related to situation awareness in aircraft maintenance teams, particularly on task performance and the prevention of mistakes. In teams, both individual situation awareness on the individual tasks, as well as shared situation awareness of the team's shared goals and interdependencies between tasks can be distinguished. One of the findings from this research is the lack of information provision to the mechanics. Without this information they are not able to perform key functions of teams, such as helping each other out or swapping tasks. With an increased understanding of the organizational goals, the mechanics would be able to make better decisions in line with organizational expectations.

Case-Based Reasoning
Another social aspect related to situations and the environment is case-based reasoning, in which a person remembers similar situations to the current situation and uses these situations to solve the current problem [250]. A case represents specific knowledge, related to a specific situation, when general knowledge is unavailable [250]. The concept of case-based reasoning was constructed during research that aimed at understanding how people remember information and retrieve this information [251]. It was found that people often solve problems by remembering how they solved similar problems [251]. Explanations by humans are sometimes also constructed by remembering a similar case, using its explanation and adapting it to the current situation [252].

Kolodner [250] argues that the quality of a case-based reasoner depends on its experiences, its ability to understand new situations based on these experiences, its ability to adapt, its ability to evaluate and its ability to memorize experiences in the right way. This relates to the general deliberation process of a case-based reasoner that is presented by Dignum and Dignum [253]:

1. Formulate the problem
2. Retrieve former experiences
3. Use these experiences for problem solving
4. Revise the new obtained experience
5. Memorize (the evaluation of) this new experience

Kolodner [252] elaborates on the advantages and disadvantages of case-based reasoning techniques. It allows for a quick deliberation process, since answers do not have to be constructed from the beginning. Secondly, it allows for finding solutions to problems that the reasoner does not understand completely. Case-based reasoning can be helpful in preventing to repeat a past mistake. Furthermore, it can provide a method for finding solutions to a problem when no systematic method is available.

However, it can be dangerous for a reasoner to rely on an old case without properly validating its use to the new situation. People are often not reminded of all applicable past experiences during reasoning. A drawback of using case-based reasoning in social simulation is that it is hard to find an algorithm that could calculate the revision of plans accurately. Moreover, a large case base is needed to provide agents with enough information to reason correctly. In some instances it is not possible to generate such a large case base (due to the severity of the consequences for example). Simulation could be a solution to generate these cases and provide decision-makers with a more elaborate case base.

Social Practise Theory
Another concept that is used to explain human decision-making involves the concept of social practises. Social Practise Theory originated from Wittgenstein and Heidegger, who aimed at describing the world from the viewpoint of practises (daily actions) instead of the agency (the individual) or social structures (organizations) [254].

In social science, practises were either explained as a personal habit [255] or a social act [256]. Reckwitz [257] combined these two notions of practises in the concept of social practices, which are everyday practices and are typically habitually performed in a society. The social aspect of these practises lies in the similarity between individuals, at different moments in time and environments [257]. Reckwitz [257]'s conception of social practises underlies most studies within Social Practice Thoery.

Present-day research on Social Practise Theory is all based on Giddens [258]'s adaptive structuration theory, that aims at finding a balance between the individual and structure. The use of Social Practise Theory in social (simulation) research can be key in connecting actions and the environment within larger social systems. Most researchers in Social Practise Theory use Shove et al. [259]'s conception of the three core elements for social practises:

- *Materials:* the physical elements that are needed to perform a practise.
- *Meanings:* the beliefs, values, intentions and emotions that are related to the material.
- *Competence:* the skills or knowledge that is needed to perform the practise.

Social practises can form bundles of interrelated practises [259, 260]. These elements influence the enactment of social practises, but these activities also influence these elements, and change the social practises dynamically [261]. Social interaction can also influence these elements, creating shared social practises, that can serve as a common ground for coordination between agents [253]. Mercuur et al. [254] provided a framework for the sharedness of social practises in three different ways:

- *Habits:* the repetition of behaviour as a response to a regular experienced context [262].
- *Social intelligence:* the way that people act in a shared world [254].
- *Interconnected activities:* the connection of these activities, w both temporal or causal [254].

6 Conclusions

This chapter presents the final conclusions of this literature research, with an overview of the most significant findings that could be of interest for the research proposal.

Task Allocation in Aircraft Maintenance - Research into the task allocation processes for aircraft maintenance is scarce. Task allocation encompasses the way that tasks are chosen, assigned and coordinated among people. Other maintenance planning processes, such as task scheduling and resource allocation were more available. The main literature gaps were:

- A lack of bottom-up approaches instead of top-down optimization approaches.
- A lack of short term planning in contrast to the strategic and tactical planning phases.
- A lack of the mechanics' perspective and social factors in aircraft maintenance literature.

These literature gaps drove the need for understanding these different aspects and a more thorough literature study on the available methods and research to contribute to these existing gaps. It was argued that these gaps all relate to a dynamic environment, with local information, that requires bottom-up models and tools. That why the field of Distributed Artificial Intelligence is of importance.

Distributed Artificial Intelligence - Agent-based modeling was found to be most applicable for modeling and simulation of these task allocation procedures. The main advantage is that it allows to capture emergent phenomena and is well suited for social simulation. Many different agent architectures exist and even more specification languages as well as implementation tools. Verification and validation of agent-based models, specifically in social simulation, is however difficult. A field of interest within agent-based modeling and multi-agent systems is the use of integrative agents, which can support humans in many of their doings based on their personality, mental states or environment. This integration of agents in human decision-making asks for the alignment of decisions between people and agents. A research field of interest for this application is Explainable Artificial Intelligence, which aims to explain decision-making by automated systems to humans in an understandable way.

Negotiations - In order for self-motivated agents with individual goals to coordinate, negotiation is necessary. The main negotiation mechanisms that could be used are contract net protocols, auctions, bargaining and voting. Three phases are generally distinguished for modeling negotiation processes. The first phase is the process of resource valuation, which is driven by and generally modeled using economic theories. Secondly, decision theory is used to model decision-making in negotiation. Three main methods for decision theory are distinguished: game theory, heuristic methods and argumentation-based negotiation. The assumption of rational behaviour makes game theoretic approaches unsuitable for this research. Heuristic methods and argumentation-based negotiation both allow for modeling bounded rationality and could therefore be of interest for social simulation. Another advantage of argumentation-based methods is that it allows for straightforward explanations. The final phase revolves around the negotiation agreement and outcomes. Integrated agent models can be of interest for this research. Negotiation Support Systems could support mechanics with decision-making.

Social Simulation - An understanding of human bounded rationality as well as the observed social elements of task allocation and execution in aircraft maintenance led to the understanding that current task allocation methods lack a social perspective. Challenges for social simulation are that formal modeling is hard (and sometimes impossible), explaining outcomes as well as validating these results can be even more difficult, and generalizing these explanations to real-wold processes can be risky. However, social simulation can provide a new perspective of social processes that allows for a better understanding of the mechanisms involved. Several social factors have been identified and researched that could be of importance for this research into task allocation in aircraft maintenance. Two of these aspects are believed to be essential: teaming and social practises.

Teaming Aspects - Aircraft maintenance tasks are performed in teams, which allows mechanics to: constantly monitor progress of the team efforts as a whole, coordinate actions such that these do not interfere with each other, communicate failures and successes in order for the system to be more successful and to help each other out when needed. Since aircraft are extremely complex, teams embrace the specialization of mechanics in different expertise's, which allows for collectively finishing all maintenance activities. These differences in expertise and experience could however lead to power structures and relations within this team. Power relations, and even more important, social influence lays at the foundation of the dynamics within teams. Furthermore, social research into team dynamics emphasized the importance that supporting technology should accommodate social practises of teams, such as making decisions, but also teaching and socializing, or establishing power relations.

Social Practises - Social practises have also been of increasing interest in social simulation research. Social Practise Theory aims to look at the world from the perspective of (daily) activities, called practises. This is in contrast to most conventional methods that look from the individual or organizational perspective. Social practises allow for a better integration of actions and the environment. Besides, social practises can also influence other people, which creates shared social practises. These shared social practises can then serve as common ground for coordination between agents. Several frameworks for Social Practise Theory application in social simulation are presented. The research area is however relatively new and validation of the existing models is still lacking.

7 Research Approach

This chapter presents a summary of the research approach that has been defined based on the literature study. Moreover, the methodological approach for executing this research has been introduced.

The literature research in this report revealed several literature gaps for bottom-up task allocation in aircraft maintenance. Although many approaches could be applicable in order to address these gaps, the previous section elaborates on the specific elements that were believed by the author to be particularly of interest for the specific problem of task allocation in aircraft maintenance. Combining these separate elements leads to the following research question:

> **What is the relationship between the social aspects of teamwork and the performance of task allocation methods in aircraft maintenance?**

Sub questions will assist the author in shaping the thought process as well as generating manageable work-packages for the execution of this research. The following sub-questions are formulated:

1. What domain knowledge could be useful for evaluating conventional task allocation methods as well as negotiation on task allocation in aircraft maintenance teams?
2. How could the characteristics of agents, environment and their interactions within the task allocation environment be modeled?
3. How does a conventional task allocation method impact team performance?
4. How does the process of negotiation on task allocation, explicitly considering social teaming aspects, impact team performance?
5. How could the results from (3) and (4) present insights into the impact of social teaming aspects on the performance of task allocation methods within aircraft maintenance teams?

The following methodological steps have been identified for the execution of the research project:

1. Work Package 1: Initial Hypotheses and Research Scope
2. Work Package 2: Conceptual Model Development
3. Work Package 3: Formal Model Development
4. Work Package 4: Model Implementation and Simulation
5. Work Package 5: Result Analysis, Validation and Conclusion

III

Supporting Work

8 Theoretical Elaboration

This chapter elaborates on the theoretical content that has been considered in this research. The first section will provide additional insights on the purpose of social simulation. The second outlines the main definitions that have been used in this research.

8.1. The Purpose of Social Simulation

Social simulation has been around for about 20 years [202]. Yet, there is no all-encompassing framework for developing, analyzing and explaining these simulations. Moreover, there is no agreement on the purpose of social simulation among scientists. This section will therefore briefly elaborate on the different views on the purpose of social simulation and the theoretical foundations underlying this study.

There is no general agreement on whether social simulation should be used as a way of constructing social theories or as performing virtual experiments [202]. Some argue that building computer simulations requires rigorously specified axioms in contrast to theorizing in sociology [208]. A simulation could require filling in gaps that are needed for the simulation to work and therefore reveal gaps in a theory [202]. Others argue that social simulations are needed to test a social theory. In these simulations, a model simulates a social phenomenon and is modified to create different conditions that can be compared [202]. Performing these experiments in the real world is often impossible. The simulation is therefore used to generate data that can help in building theories [202]. This study is of the latter type: the simulations have been used for different experiments to uncover and explain relationships between the local social properties and the global task allocation performance in aircraft maintenance teams.

Some researchers argue that an explanation in social science requires identifying social laws [202]. Social laws, if they exist, always have exceptions. The current trend is more shifting to the mechanism approach, which aims at sufficiently describing the underlying mechanism that cause a certain observed phenomenon [202]. The question is however when a causal explanation is sufficient. Sawyer [202] illustrates this with an example of the ideal gas law. In the mechanistic approach, the location and movement of all molecules is necessary to explain pressure. The ideal gas law is therefore not sufficient in explaining the behavior of a gas. There is a fine line between identifying and explaining relations in social simulation models. In this research specific variables impacting model behavior and global properties have been identified and explained as much as possible.

8.2. Definitions

Often many definitions of a concept are presented in social science. In order to ensure consistency, Table 8.1 provides an overview of the definitions for this research in alphabetical order.

Table 8.1: Definitions of social concepts

Concept	**Definition**
Agent	”A computer system, situated in an environment and capable of autonomous action in this environment in order to meet its objectives” [54]
Causality orientation	”The extent to which people are self-determined in general” [213]
Coercive power	”Power based on the possibility of penalties” [235]
Compliance	”A response to a request, in which a person recognizes to be urged to respond in a desired way” [230]
Effort	”The physical or mental activity needed to achieve something” [263]
Expert power	”Power based on knowledge or expertise” [235]
Extrinsic motivation	”Motivation for an activity in order to attain some separable outcome [264]
Flow	”An intense focus and concentration” [265]
Group	”A number of people or things that are put together or considered as a unit” [266]
Impression	”An idea, feeling, or opinion about something or someone, especially one formed without conscious thought or on the basis of little evidence” [267]
Intrinsic motivation	”The motivational instantiation of the proactive, growth-oriented nature of human beings” [207]
Legitimate power	”Power based on internalized values of the submissive” [235]
Mastery	”Reaching one’s inner potential” [268]
Motivation	”The degree to which an individual is ’moved’ to do something” [212]
Need for autonomy	”The desire to obtain a feeling of being in control of one’s own actions” [207]
Need for competence	”The desire to be competent in one’s actions, skills and desires” [207]
Need for esteem	”The desire for a high evaluation of one’s self based on achievement” [269]
Need for relatedness	”The desire to experience a sense of belonging to and interaction with others” [207]
Need for safety	”The desire to work safely and prevent mistakes or injuries” [269]
Negotiation	”A non-individual decision-making process, which involves two or more parties that jointly determine outcomes of mutual interest to resolve a dispute via exchanging ideas, arguments and offers” [107]
Performance	”How well a person, machine, etc. does a piece of work or an activity” [270]
Persuasive power	”Power based on persuasion capabilities” [235]
Power	”The capacity or ability to change the beliefs, attitudes, or behaviors of others” [271]
Referent power	”Power based on relatedness” [235]
Reputation	”A perception that someone has of another’s intentions and norms” [272]
Reward power	”Power based on resources” [235]
Situation awareness	”The level of awareness an agent has of a situation: the dynamic understanding of what is going on” [247]
Shared cognition	”The collective cognitive activity of individuals where the collective activity has an impact on the group goals and activities” [273]
Shared situation awareness	”The degree to which team members have the same situation awareness on shared situation awareness requirements” [274]
Skill level	”Level of an ability to do something” [275]
Social influence	”A process in which people’s attitudes, opinions, beliefs, or behavior are altered or controlled by some form of social communication, including conformity, compliance, obedience, persuasion and influence of social norms” [231]
Task	”A piece of work that has to be done, especially one regularly, unwillingly or with difficulty” [276]
Task allocation	”The way that tasks are chosen, assigned, and coordinated” [277]
Team	”A group in which people are restricted to having a common goal of some sort and typically cooperate and assist each other in achieving their common goal” [59]
Theory of mind	”The ability of individuals to reason about the thoughts, beliefs and feelings of others to predict behavioral responses” [91]
Thoroughness	”A large amount of care and attention to detail” [278]
Time efficiency	”Performing in the best possible manner with the least waste of time” [279]
Time pressure	”The subjective feeling of having less time than is perceived to be required to complete a task and be motivated to complete the task in the available time” [280]
Trust	”A psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another” [281]
Wisdom of crowds	”The phenomenon that the average judgement in a group converges to the accurate solution” [282]

9

Model Elaboration

This chapter presents additional information on the proposed model. The first section will elaborate on the underlying model assumptions. The second section presents additional properties for the simulation with multiple shifts working on the maintenance tasks. The third section provides an overview of the variable ranges and their respective meanings.

9.1. Model Assumptions

The following main assumptions underlie the proposed model:

Task duration uncertainty - It is assumed that maintenance organizations are dealing with a lack of up to date information on the duration of maintenance tasks. This is in line with mechanics' reports that task execution times depend on the performance of the mechanic executing the task.

No personal preferences - The model aims to investigate the group decision-making process towards the team's common goals of performing the tasks as soon and as safe as possible. It is therefore not considered that agents can have personal preferences for specific tasks or fellow team members.

No skill types - It is assumed that all mechanics have the same skill types. A main landing gear replacement mostly involves mechanical tasks and does not require any specific specialties, such as avionics or sheet work. That is why only skill levels are considered in this model.

Effort as important as skill - Skills are more often considered in decision-making models rather than effort. The maintenance work depends, however, not only on skill levels, but also on mechanics' willingness to work in a desired way. The authors believe that this is mostly due to the variation in people's effort. That is why this model also considers effort and assumes efficiency and thoroughness effort to be of equal importance for successful task execution as skill level.

Efficiency and thoroughness independence - Efficiency and thoroughness effort are in general intertwined, according to the efficiency-thoroughness trade-off. In this model, however, no property has explicitly considered this relationship. This is due to the requirement of independent issues in additive utility functions. That is why agents do not have a high efficiency and thoroughness goal simultaneously.

Personal goals in group context - The agent goals are not only representing their individual aims for effort and skill, but also capture their goals for the entire team. The mastery goal therefore also considers the agent's motivation for the entire group at reaching their inner potential.

Social comparison influence - There is no clear answer in social comparison theory about the direction of comparative influence [283]. A person can be judged less skilled in the context of extremely skilled people, than in then context of less skilled people [284]. Sometimes, however, comparison leads to opposing outcomes: people evaluate their own self more skilled after comparison with a skilled person than with a less skilled person [285]. The social contagion theory assumes that people are assimilated towards a given standard. Impression formation as well as reputation and trust hold the same assumption in this model. It is therefore also assumed that a mechanic will view the efforts of other mechanics positive when these are higher than its own effort and vice verse.

Time pressure - The model assumes that the team lead has a level of experienced time pressure, based on its information on the current task execution progress, and communicates this with the other agents. It is assumed that the other agents do not have the relevant information to know which tasks have been completed and which tasks still need to be performed.

Minimizing under-competence - It is assumed that all agents aim for minimizing under-competence when evaluating the task allocation options. The agents want to make sure that at least the minimum required task demands are satisfied.

Team lead expertise - The team lead is not assumed to be any more experienced in judging the capabilities and efforts of its fellow team members. Moreover, the team lead does not encounter the mechanics more often by checking up on them.

Limited number of voting options - The voting protocol assumes that people are not capable of evaluating large numbers of options accurately. That is why the agents only vote on 10 proposed options.

Collusion within groups - It is assumed that only old or new mechanics will be inclined to collude with fellow group members. The power relations in these groups are assumed to be similar. Agents do not have any incentive to manipulate when their combined utility will not increase by colluding.

Safety criticality - The safety criticality of a task is assumed to be driven by the effort, time and resources needed to undo the safety incident. It is assumed that all mistakes are noticed during task execution and the aircraft leaves the hangar free of any mistakes or damages.

Desired reputation within theory of mind - Mechanics are assumed to aim for having a reputation in line with their efforts. If mechanics believe that they have a higher reputation than their internal goal, they will generate less effort, since they do not specifically aim for such a high reputation. The other way around, if their goal is higher than their believed reputation, they are assumed to increase their effort to obtain their desired reputation within the team.

9.2. Model Specification: Shift Changes

This section provides the additional properties that have been used for modeling multiple shifts for the complete main landing gear replacement. These have been outlined in the three before-mentioned categories of an agent-based model specification. There have not been any changes to the environment specification, so the next sections will describe the additional properties for the agent characteristics, interactions between agents and interactions between agents and the environment.

9.2.1. Agent Characteristics

All agents have two additional characteristics for the model with multiple shifts. The first is that all agents have a belief about the current team, ct, that is performing tasks. Furthermore, the agents have a belief about the current shift, cs, of agents. The main landing gear replacement should be finished in 6 shifts, performed by 3 different teams. The team lead agents have two additional beliefs. First, they have a belief on whether a shift change is happening, shc. If agents are not part of the current team, they have additional persistence properties, which is elaborated on next.

Persistence properties - If agents do not believe that they are part of the current team, they will not execute the previously mentioned properties, and only have persistence properties for their characteristics, such as efficiency effort, thoroughness effort, skill, reputation and trust.

9.2.2. Interactions between Agents

During shift changes, the agents have interactions with agents from other teams. Moreover, they need to start with the task execution where the previous team has finished. Furthermore, the team lead agents of both teams communicate on the task execution progress. These three types of properties will be elaborated on below.

Social influence and trust - The social influence and trust properties that have been outlined before still hold during shift changes. Nevertheless, during a shift change, an agent encounters specific agents at certain time points, rather than randomly its own team members or an agent that it is working with. Table 9.1 shows for every moment in time during a shift change, which agents encounter one another.

The new team members enter the hangar at time t_{shift} and consecutively communicate with the team lead about the task packages and planning. Afterwards, voting starts and the agents interact with their own team members randomly. After task allocation, the previous team members update the new team on the progress of their task sets. The new team members then start executing the tasks.

Table 9.1: Agent encounters during shift changes

Time	Team 1	Team 2
t_{shift}	Own team members randomly	Own team lead
$t_{shift}+1$	Own team members randomly	Own team lead
$t_{shift}+2$	Own team members randomly	Own team members randomly
$t_{shift}+3$	Own team members randomly	Own team members randomly
$t_{shift}+4$	Agent team 2 with the same task set	Agent team 1 with the same task set
$t_{shift}+5$	Agent team 2 with the same task set	Agent team 1 with the same task set

Task communication - If an agent of a new shift starts executing a task, and the agent with that task set in the previous shift has not yet finished, it will start where that agent was left. This is illustrated in Equation 9.1, where agent j is part of the first shift and agent i part of the second shift.

$$p_{f,i}^{t_{shift}+5} = p_{f,j}^{t_{shift}+4} \tag{9.1}$$

Team lead communication - At the time point before all other agents arrive, $t_{shift}-1$, the team lead of the new shift communicates with the previous team lead. This previous team lead j communicates the current state of the task execution as well as its experienced time pressure to the new team lead i. Team lead i updates its beliefs according to Equations 9.2 and 9.3. etp_i^t is agent i's experienced time pressure at time t, $goal_i(re)$ is agent i's relatedness goal, γ_{ji} the power influence of team lead j on team lead i and tp_i is team lead i's belief on the task packages that need to be performed by everyone.

$$etp_i^{t+1} = etp_i^t + \gamma_{ji} \cdot goal_i(re) \cdot (etp_j^t - etp_i^t) \tag{9.2}$$

$$tp_i^{t+1} = tp_j^t \tag{9.3}$$

9.2.3. Interactions between Agents and the Environment

Additional interactions between agents and the environment represent the agents' interactions with time. The first set of properties holds for all agents. The other property is only valid for the team lead.

Shift change properties all agents- All agents update their beliefs on the current team and shift according to Equations 9.4 and 9.5 at the start of a shift change. This holds until a new shift change starts. ct_i^t is agent i's belief about the current team at time t and cs_i^t its belief about the current shift.

$$ct_i^{t+1} = \begin{cases} ct_i^t + 1 & \text{if } t = t_{shift} \ \wedge \ ct_i^t \neq 3 \\ 1 & \text{if } t = t_{shift} \ \wedge \ ct_i^t = 3 \\ ct_i^t & \text{else} \end{cases} \tag{9.4}$$

$$cs_i^{t+1} = \begin{cases} cs_i^t + 1 & \text{if } t = t_{shift} \\ cs_i^t & \text{else} \end{cases} \tag{9.5}$$

Shift change properties team lead agents - The team lead agents track the time and communicate when a shift change starts. This is illustrated in Equation 9.6.

$$shc_i^{t+1} = \begin{cases} 1 & \text{if } t_{shift} \ \leq \ t \leq t_{shift}+5 \\ 0 & \text{else} \end{cases} \tag{9.6}$$

9.3. Variable Meanings

This section describes the meaning of the different ranges for the variables that have been introduced in this model. Table 9.2 illustrates these ranges for the agent variables and Table 9.3 for task variables.

Table 9.2: Meaning of agent variable ranges

Variable	**Meaning [0.1,0.4]**	**Meaning [0.4,0.7]**	**Meaning [0.7,1.0]**
$goal(eff)$	Does not aim much for time efficient task execution at all	Aims for time efficient task execution, but not at the cost of thoroughness	Aims for time efficient task execution above everything
$goal(tho)$	Aims for only limited thorough task execution	Aims for thoroughness, but not at the expense of efficiency	Aims for thorough task execution above everything
$goal(mas)$	Does not aim for reaching its own and the team's inner potential	Aims for reaching its own and the team's inner potential, but not above all	Aims for reaching its own and the team's inner potential above everything
$goal(au)$	Does not desire to make its own decisions and being in control	Does aim for making its own decisions but also susceptible for others' opinions	Aims at making decisions solely based on its own observations and reasoning
$goal(re)$	Does not have the desire for a sense of belonging: slightly influenced by others	Aims for a sense of belonging with team members: moderately influenced by other team members	Aims at having a sense of belonging with team members: influenced by others rather easily
$goal(es)$	Does not aim for recognition and rewards by a superior	Aims for recognition and rewards by a superior, but not above everything	Aims for recognition and rewards by a superior above everything
ef_{eff}	Limited effort for time efficiency, up to half of the estimated time extra for a task	Average effort for time efficiency, takes approximately the estimated amount of man-hours for a task	High level of effort for time efficiency, takes less than the estimated time for a task, up to half of the time
ef_{tho}	Lack of attention to thoroughness and skips safety measures often	Medium attention to thoroughness, and sometimes skips safety measures	High attention to thoroughness and skips safety measures hardly ever
sk	Has limited experience with mechanical maintenance tasks	Has average experience with the tasks of a main landing gear replacement	Has performed the main landing gear replacement tasks before, at least once
etp	Relaxed working conditions, the team has more time than needed	Normal working conditions, the team is on schedule for meeting the deadline	Stressed working conditions, the team needs to hurry to meet the deadline
$T_{i \to j}(\phi)$	Agent i does not trust that agent j is skilled enough, works efficiently or thoroughly enough	Agent i has average trust in agent j's skills, efficiency or thoroughness effort	Agent i trusts that agent j is highly skilled, works efficiently or thoroughly when desired for a task
γ_{ji}	Limited power influence of agent j on agent i, mostly based on referent power and little persuasion power	Medium power influence of agent j on agent i, mostly based on medium referent and legitimate power and optionally expert power	High power influence of agent j on agent i, mostly based on high referent and legitimate power and optionally high expert power
Variable	**Meaning [-1,0]**	**Meaning 0**	**Meaning [0,1]**
$Imp_{i \to j}(\phi)$	Agent i has a negative impression of agent j on aspect ϕ	The impression of agent i on agent j coincides with its own norms on ϕ	Agent i has a positive impression of agent j on aspect ϕ
$R_{i \to j}(\phi)$	Agent i has a negative reputation of agent j on aspect ϕ	The reputation of agent i on agent j coincides with its own norms on ϕ	Agent i has a positive reputation of agent j on aspect ϕ

Table 9.3: Meaning of task variable ranges

Variable	**Meaning [0.1,0.4]**	**Meaning [0.4,0.7]**	**Meaning [0.7,1.0]**
tho^{req}	Low level of thoroughness is needed, mostly for removal operations: f.e. remove wheels from structure	Average level of thoroughness needed, for general installation of components: f.e. install wheels to structure	High level of thoroughness needed: f.e. topping up hydraulic reservoirs or performing functional tests
sk^{req}	General skills that most mechanics have are required: f.e. jacking-up an aircraft	Tasks that can be performed by average mechanics: f.e. bleeding a braking system	Specifically high levels of skills are required: f.e. checking the condition of specific parts
sc	Simple corrective actions can fix a violation of a safety measure: f.e. lubrication tasks	Corrective actions take half of the planned work for a task: f.e. removing wheels goes wrong	A task can induce serious damage: f.e. area under landing gear is not clear when landing gear comes down
dep_f	A small amount of tasks within this shift depends indirectly on the completion of this task f	The number of dependent tasks is in the middle of the maximum and minimum within this shift	The number of dependent tasks is in the highest range for this task f, compared to the other tasks
$timer$	The team is approaching the deadline	The team is halfway through the shift	A lot of time for task execution left
mhr	There is only a limited amount of man-hours still to be performed	Half of the estimated man-hours for this shift still need to be performed	Most man-hours for this shift still need to be performed

10

Simulation Elaboration

This chapter presents elaborations on the simulation of the proposed model. Sections 10.1 and 10.2 provide an overview of the input parameters for the task and temporal parameters respectively. Elaborations on the statistical evaluation of the results can be found in Section 10.3. Additional results are presented in Section 10.4. Section 10.5 presents the agent states after model initialization.

10.1. Task Parameters

First, an overview of the task input parameters that have been used for the case study are presented. Next, an explanation of the calculation for the relative dependency variable is provided.

10.1.1. Task Input Values

The main landing gear replacement tasks were retrieved from a task card. One could distinguish six phases within the main landing gear replacement:

- A: Job Set-Up
- B: Removal
- C: Preparation of Replacement Component
- D: Installation
- E: Tests
- F: Close-Up

The variables for all involved tasks can be found in Table 10.1. Note that many tasks need to be performed for the main landing gears on both the right (R) and left-hand side (L).

10.1.2. Normalized Dependency Calculation

In order to normalize the number of dependent tasks in a shift, a general normalization function was used. For all tasks within a shift, the number of direct dependent tasks was determined from Table 10.1. The indirect number of dependent tasks was then determined by evaluating the entire chain of tasks. So for example, if task F was dependent on task D and E, and these tasks were both dependent on tasks B and C, which were on their turn dependent on task A, the number of dependent tasks on task A is equal 6, while the number of dependent tasks on task B is 3.

The normalized dependency values are then calculated according to Equation 10.1. dep_f is the normalized number of dependent tasks on task f, nde_f is the absolute number of tasks (indirectly) dependent on task f in a shift and nde_{max} is the maximum number of dependent tasks in a shift.

$$dep_f = \frac{nde_f}{nde_{max}} \quad (10.1)$$

Table 10.1: Task input values

Task	Description	mh	sk^{req}	tho^{req}	$mech$	sc	Dependent on
A.1	Set MLG control lever in down position	0.33	0.1	0.1	1	0.7	-
A.2	Set MLG freefall extension handle in normal position	0.17	0.2	0.1	1	0.5	-
A.3	Position access platforms	0.50	0.4	0.5	2	0.4	-
A.4R	Position safety barriers at gear door travel ranges	0.33	0.4	0.4	1	0.8	-
A.4L	Position safety barriers at gear door travel ranges	0.33	0.4	0.4	1	0.8	-
A.5R	Open main gear doors	0.08	0.2	0.8	1	0.3	A.1, A.2, A.3, A.4R
A.5L	Open main gear doors	0.08	0.2	0.8	1	0.3	A.1, A.2, A.3, A.4L
A.6	Depressurize green hydraulic system	0.33	0.7	0.8	1	0.8	A.5R, A.5L
A.7	Depressurize yellow hydraulic system	0.33	0.7	0.8	1	0.8	A.5R, A.5L
A.8	Depressurize green and hydraulic reservoirs	0.33	0.7	0.5	1	0.8	A.6, A.7
A.9	Open, safety and tag circuit brakers	0.50	0.2	0.6	1	0.9	A.8
A.10	Jack up aircraft until wheels are clear of ground	1.00	0.7	0.8	4	0.9	A.9
A.11R	Remove four wheels from right MLG	2.67	0.2	0.3	2	0.5	A.10
A.11L	Remove four wheels from left MLG	2.67	0.2	0.3	2	0.5	A.10
A.12R	Remove brake units from right MLG	2.67	0.2	0.3	2	0.4	A.11R
A.12L	Remove brake units from left MLG	2.67	0.2	0.3	2	0.4	A.11L
A.13R	Remove wheel tachometers right MLG	0.50	0.2	0.3	1	0.3	A.12R
A.13L	Remove wheel tachometers left MLG	0.50	0.2	0.3	1	0.3	A.12L
A.14R	Disconnect secondary door control rod of MLG leg	0.33	0.2	0.3	1	0.5	A.13R
A.14L	Disconnect secondary door control rod of MLG. Leg	0.33	0.2	0.3	1	0.5	A.13L
A.15R	Remove cylinder door	0.33	0.5	0.5	1	0.5	A.9
A.15L	Remove cylinder door	0.33	0.5	0.5	1	0.5	A.9
A.16R	Position hydraulic fluid container	0.17	0.1	0.1	1	0.1	A.13R, A.15R
A.16L	Position hydraulic fluid container	0.17	0.1	0.1	1	0.1	A.13L, A.15L
B.1R	Disconnect aircraft systems at main gear attachment point	1.00	0.3	0.7	1	0.6	A.16R
B.1L	Disconnect aircraft systems at main gear attachment point	1.00	0.3	0.7	1	0.6	A.16L
B.2R	Disconnect actuating cylinder and main gear leg	0.33	0.3	0.3	1	0.5	B.1R
B.2L	Disconnect actuating cylinder and main gear leg	0.33	0.3	0.3	1	0.5	B.1L
B.3aR	Mark and disconnect hydraulic lines on actuating cylinder	0.67	0.5	0.7	1	0.7	B.2R
B.3aL	Mark and disconnect hydraulic lines on actuating cylinder	0.67	0.5	0.7	1	0.7	B.2L
B.3bR	Position hoisting device on actuating cylinder	0.33	0.4	0.6	2	0.4	B.3aR
B.3bL	Position hoisting device on actuating cylinder	0.33	0.4	0.6	2	0.4	B.3aL
B.3cR	Attach hoisting equipment to structure	0.33	0.4	0.6	1	0.4	B.3bR
B.3cL	Attach hoisting equipment to structure	0.33	0.4	0.6	1	0.4	B.3bL
B.3dR	Position minilift	0.33	0.2	0.5	2	0.2	B.3cR
B.3dL	Position minilift	0.33	0.2	0.5	2	0.2	B.3cL
B.3eR	Remove pints, nuts and bolds and lubricate	0.50	0.2	0.3	1	0.1	B.3dR
B.3eL	Remove pints, nuts and bolds and lubricate	0.50	0.2	0.3	1	0.1	B.3dL
B.3fR	Disengage actuating cylinder eye from trunnion	0.17	0.2	0.3	1	0.1	D.3eR
B.3fL	Disengage actuating cylinder eye from trunnion	0.17	0.2	0.3	1	0.1	D.3eL
B.3gR	Temporarly attach all parts on structure	0.17	0.1	0.8	1	0.3	B.3fR
B.3gL	Temporarly attach all parts on structure	0.17	0.1	0.8	1	0.3	B.3fL
B.4R	Disconnect locking springs from attachments	0.67	0.7	0.6	2	0.5	B.3gR
B.4L	Disconnect locking springs from attachments	0.67	0.7	0.6	2	0.5	B.3gL
B.5aR	Install hoisting clamp on brace strut	0.17	0.6	0.6	1	0.3	B.4R
B.5aL	Install hoisting clamp on brace strut	0.17	0.6	0.6	1	0.3	B.4L
B.5bR	Position minilift	0.33	0.2	0.5	1	0.2	B.5aR
B.5bL	Position minilift	0.33	0.2	0.5	1	0.2	B.5aL
B.5cR	Install brace strut handling fixture	0.33	0.4	0.6	1	0.4	B.5bR
B.5cL	Install brace strut handling fixture	0.33	0.4	0.6	1	0.4	B.5bL
B.5dR	Remove pins, nuts and bolds and brace strut fitting	0.67	0.2	0.3	1	0.2	B.5cR
B.5dL	Remove pins, nuts and bolds and brace strut fitting	0.67	0.2	0.3	1	0.2	B.5cL
B.5eR	Fold brace strut and attach to upper arm	0.17	0.6	0.6	1	0.3	B.5dR
B.5eL	Fold brace strut and attach to upper arm	0.17	0.6	0.6	1	0.3	B.5dL
B.6R	Remove rubber coating at bearings	0.33	0.3	0.8	1	0.1	B.5eR
B.6L	Remove rubber coating at bearings	0.33	0.3	0.8	1	0.1	B.5eL
B.7R	Mark parts coated with sealant	0.33	0.1	0.6	1	0.2	B.6R
B.7L	Mark parts coated with sealant	0.33	0.1	0.6	1	0.2	B.6L

Task	Description	mh	sk^{req}	tho^{req}	$mech$	sc	Dependent on
B.8R	Depressurize shock absorber	0.50	0.8	0.5	2	0.7	B.7R
B.8L	Depressurize shock absorber	0.50	0.8	0.5	2	0.7	B.7L
B.9R	Position mean gear handling trolley and secure leg	1.00	0.9	0.9	2	0.9	B.8R
B.9L	Position mean gear handling trolley and secure leg	1.00	0.9	0.9	2	0.9	B.8L
B.10aR	Remove pins, nuts and two-half seals	0.25	0.2	0.2	1	0.3	B.9R
B.10aL	Remove pins, nuts and two-half seals	0.25	0.2	0.2	1	0.3	B.9L
B.10bR	Remove lubrication and check condition seals, replace if necessary	1.00	0.8	0.7	1	0.6	B.10aR
B.10bL	Remove lubrication and check condition seals, replace if necessary	1.00	0.8	0.7	1	0.6	B.10aL
B.10cR	Remove grease nipples, screws and half-seals	0.33	0.2	0.3	1	0.3	B.10bR
B.10cL	Remove grease nipples, screws and half-seals	0.33	0.2	0.3	1	0.3	B.10bL
B.10dR	Maneuvre handling trolley to shock strut eye end	0.83	0.3	0.8	2	0.9	B.10cR
B.10dL	Maneuvre handling trolley to shock strut eye end	0.83	0.3	0.8	2	0.9	B.10cL
B.10eR	Disengage trunnion from spherical bearing	0.50	0.8	0.8	2	0.9	B.10dR
B.10eL	Disengage trunnion from spherical bearing	0.50	0.8	0.8	2	0.9	B.10dL
B.10fR	Remove and discard grease seal	0.02	0.2	0.3	1	0.6	B.10eR
B.10fL	Remove and discard grease seal	0.02	0.2	0.3	1	0.6	B.10eL
C.1R	Remove protective coverings of replacements landing gear leg	1.50	0.2	0.3	2	0.1	-
C.1L	Remove protective coverings of replacements landing gear leg	1.50	0.2	0.3	2	0.1	-
C.2R	Remove axle protection and install on new leg	0.50	0.6	0.4	1	0.1	B.10fR, C.1R
C.2L	Remove axle protection and install on new leg	0.50	0.6	0.4	1	0.1	B.10fL, C.1L
C.3R	Install replacement landing gear leg on trolley (remove other)	2.00	0.7	0.4	2	0.8	C.2R
C.3L	Install replacement landing gear leg on trolley (remove other)	2.00	0.7	0.4	2	0.8	C.2L
C.4R	Remove safety and servo valves of removed leg	0.50	0.2	0.3	1	0.1	B.10fR
C.4L	Remove safety and servo valves of removed leg	0.50	0.2	0.3	1	0.1	B.10fL
C.5R	Install safety and servo valves on replacement leg	0.50	0.7	0.4	1	0.1	C.4R
C.5L	Install safety and servo valves on replacement leg	0.50	0.7	0.4	1	0.1	C.4L
C.6R	Clean all parts and dry with compressed air	2.00	0.1	0.6	2	0.1	C.3R
C.6L	Clean all parts and dry with compressed air	2.00	0.1	0.6	2	0.1	C.3L
C.7R	Check condition of all parts to installed and replace if necessary	0.50	0.8	0.8	1	0.7	C.6R
C.7L	Check condition of all parts to installed and replace if necessary	0.50	0.8	0.8	1	0.7	C.6L
C.8R	Position landing gear leg at its attach fittings	0.50	0.7	0.4	2	0.5	C.7R, C.5R
C.8L	Position landing gear leg at its attach fittings	0.50	0.7	0.4	2	0.5	C.7L, C.5L
D.1R	Position landing gear leg on engagement of trunnion	0.67	0.6	0.6	2	0.5	C.8R
D.1L	Position landing gear leg on engagement of trunnion	0.67	0.6	0.6	2	0.5	C.8L
D.2R	Install guiding tool on trunnion	0.33	0.5	0.7	1	0.1	D.1R
D.2L	Install guiding tool on trunnion	0.33	0.5	0.7	1	0.1	D.1L
D.3R	Position spherical bearing	0.33	0.7	0.7	1	0.7	D.2R
D.3L	Position spherical bearing	0.33	0.7	0.7	1	0.7	D.2L
D.4R	Smear trunnion and spherical bearing surfaces	0.33	0.2	0.4	1	0.3	D.3R
D.4L	Smear trunnion and spherical bearing surfaces	0.33	0.2	0.4	1	0.3	D.3L
D.5R	Enter trunnion in spherical bearing using handling trolley	0.50	0.7	0.7	2	0.7	D.4R
D.5L	Enter trunnion in spherical bearing using handling trolley	0.50	0.7	0.7	2	0.7	D.4L
D.6R	Push home trunnion in spherical bearing and remove guiding tool	0.50	0.8	0.7	2	0.3	D.5R
D.6L	Push home trunnion in spherical bearing and remove guiding tool	0.50	0.8	0.7	2	0.3	D.5L
D.7R	Install and safety half-seals with screws	0.67	0.4	0.6	1	0.4	D.6R
D.7L	Install and safety half-seals with screws	0.67	0.4	0.6	1	0.4	D.6L
D.8R	Blank greaseway holes using grease nipple	0.33	0.2	0.2	1	0.1	D.7R
D.8L	Blank greaseway holes using grease nipple	0.33	0.2	0.2	1	0.1	D.7L
D.9R	Push home trunnion in spherical bearing	0.17	0.2	0.4	1	0.3	D.8R
D.9L	Push home trunnion in spherical bearing	0.17	0.2	0.4	1	0.3	D.8L
D.10R	Guide shock strut eye end fitting into structural clevis	0.33	0.8	0.7	2	0.5	D.9R
D.10L	Guide shock strut eye end fitting into structural clevis	0.33	0.8	0.7	2	0.5	D.9L
D.11aR	Smear hinge shaft bearing surface with grease	0.50	0.2	0.4	1	0.2	-
D.11aL	Smear hinge shaft bearing surface with grease	0.50	0.2	0.4	1	0.2	-
D.11bR	Install hinge shaft with lubrication insert	0.50	0.6	0.4	1	0.4	D.10R, D.11aR
D.11bL	Install hinge shaft with lubrication insert	0.50	0.6	0.4	1	0.4	D.10L, D.11aL
D.11cR	Smear thred of hinge shaft with grease	0.33	0.2	0.4	1	0.3	D.11bR
D.11cL	Smear thred of hinge shaft with grease	0.33	0.2	0.4	1	0.3	D.11bL
D.11dR	Install nut and tighten to 6.8 and 13.6 DaN	0.33	0.2	0.4	1	0.3	D.11cR
D.11dL	Install nut and tighten to 6.8 and 13.6 DaN	0.33	0.2	0.4	1	0.3	D.11cL

Task	Description	mh	sk^{req}	tho^{req}	$mech$	sc	Dependent on
D.11eR	Check that clearance is between 0.114 and 0.721 mm	0.17	0.6	0.9	1	0.7	D.11dR
D.11eL	Check that clearance is between 0.114 and 0.721 mm	0.17	0.6	0.9	1	0.7	D.11dL
D.11fR	Smear and install and safety two cotter pins	0.50	0.5	0.4	1	0.3	D.11eR
D.11fL	Smear and install and safety two cotter pins	0.50	0.5	0.4	1	0.3	D.11eL
D.11gR	Clean surfaces smeared with grease and apply sealant	0.33	0.5	0.4	1	0.1	D.11fR
D.11gL	Clean surfaces smeared with grease and apply sealant	0.33	0.5	0.4	1	0.1	D.11fL
D.12R	Install two half seals on spherical bearing and wirelock	0.50	0.7	0.5	1	0.4	D.11gR
D.12L	Install two half seals on spherical bearing and wirelock	0.50	0.7	0.5	1	0.4	D.11gL
D.13R	Coat identified zones during removal with sealant	0.67	0.8	0.4	1	0.2	D.12R
D.13L	Coat identified zones during removal with sealant	0.67	0.8	0.4	1	0.2	D.12L
D.14R	Install grease nipples	0.17	0.4	0.5	1	0.3	D.13R
D.14L	Install grease nipples	0.17	0.4	0.5	1	0.3	D.13L
D.15R	Remove landing gear leg handling trolley	1.00	0.6	0.8	2	0.8	D.14R
D.15L	Remove landing gear leg handling trolley	1.00	0.6	0.8	2	0.8	D.14L
D.16R	Connect brace strut to main gear leg	1.00	0.7	0.9	1	0.7	D.15R
D.16L	Connect brace strut to main gear leg	1.00	0.7	0.9	1	0.7	D.15L
D.17R	Connect locking springs to lock-link assembly	1.00	0.8	0.8	1	0.7	D.16R
D.17L	Connect locking springs to lock-link assembly	1.00	0.8	0.8	1	0.7	D.16L
D.18aR	Install all bolts, nuts, pins and apply sealant	1.33	0.7	0.8	1	0.7	D.17R
D.18aL	Install all bolts, nuts, pins and apply sealant	1.33	0.7	0.8	1	0.7	D.17L
D.18bR	Remove minilift	0.33	0.2	0.6	1	0.2	D.18aR
D.18bL	Remove minilift	0.33	0.2	0.6	1	0.2	D.18aL
D.18cR	Remove hoisting device from actuating cylinder	0.50	0.3	0.6	1	0.2	D.18bR
D.18cL	Remove hoisting device from actuating cylinder	0.50	0.3	0.6	1	0.2	D.18bL
D.18dR	Connect hydraulic lines one by one	1.00	0.6	0.5	1	0.6	D.18cR
D.18dL	Connect hydraulic lines one by one	1.00	0.6	0.5	1	0.6	D.18cL
D.19R	Connect secondary control rod on main gear leg	1.00	0.5	0.8	1	0.9	D.18dR
D.19L	Connect secondary control rod on main gear leg	1.00	0.5	0.8	1	0.9	D.18dL
D.20R	Connect actuating cylinder to main gear leg	0.33	0.6	0.6	1	0.9	D.19R
D.20L	Connect actuating cylinder to main gear leg	0.33	0.6	0.6	1	0.9	D.19L
D.21R	Connect gear leg to structure	0.67	0.7	0.6	1	0.9	D.19R
D.21L	Connect gear leg to structure	0.67	0.7	0.6	1	0.9	D.19L
D.22R	Install cylinder door	0.50	0.6	0.5	1	0.8	D.20R, D.21R
D.22L	Install cylinder door	0.50	0.6	0.5	1	0.8	D.20L, D.21L
D.23R	Install wheel tachometers	0.67	0.5	0.5	1	0.8	D.22R
D.23L	Install wheel tachometers	0.67	0.5	0.5	1	0.8	D.22L
D.24R	Install brake units	2.67	0.5	0.6	2	0.9	D.23R
D.24L	Install brake units	2.67	0.5	0.6	2	0.9	D.23L
D.25R	Install wheels	2.67	0.5	0.6	2	0.9	D.24R
D.25L	Install wheels	2.67	0.5	0.6	2	0.9	D.24L
D.26R	Charge pitch damper	1.00	0.6	0.5	1	0.8	D.25R
D.26L	Charge pitch damper	1.00	0.6	0.5	1	0.8	D.25L
D.27R	Charge shock absorber	1.00	0.6	0.5	1	0.8	D.26R
D.27L	Charge shock absorber	1.00	0.6	0.5	1	0.8	D.26L
D.28R	Bleed normal braking system	2.00	0.7	0.5	2	0.6	D.27R
D.28L	Bleed normal braking system	2.00	0.7	0.5	2	0.6	D.27L
D.29R	Bleed alternate braking system	2.00	0.7	0.5	2	0.6	D.28R
D.29L	Bleed alternate braking system	2.00	0.7	0.5	2	0.6	D.28L
D.30R	Carry out lubrication operations	1.00	0.5	0.6	1	0.5	D.29R
D.30L	Carry out lubrication operations	1.00	0.5	0.6	1	0.5	D.29L
E.1	Functional test of normal landing gear	1.00	0.6	0.9	3	0.8	D.30R, D.30L
E.2	System test with shock absorbers compressed	1.00	0.6	0.9	3	0.8	E.1
E.3	Functional test of landing gear Free Fall extension	1.00	0.6	0.9	3	0.8	E.2
E.4	Normal braking operational test	1.00	0.6	0.9	3	0.8	E.3
E.5	Test of braking upon main gear touch down	1.00	0.6	0.9	3	0.8	E.4
E.6	Operational test of alternate braking system	1.00	0.6	0.9	3	0.8	E.5

Task	Description	mh	sk^{req}	tho^{req}	$mech$	sc	Dependent on
F.1R	Remove hydraulic fluid container	0.33	0.1	0.2	1	0.2	E.6
F.1L	Remove hydraulic fluid container	0.33	0.1	0.2	1	0.2	E.6
F.2	Make certain that working area is clean and. clear of tools	1.00	0.1	0.8	1	0.9	E.6
F.3	Lower the aircraft on its wheels	1.33	0.8	0.8	4	0.8	F.1R, F.1L, F.2
F.4	Remove safety tags and close circuit brakers	1.00	0.5	0.5	1	0.5	F.3
F.5	Pressurize hydraulic reservoirs	0.33	0.7	0.8	1	0.7	F.3
F.6	Close main gear doors	0.33	0.5	0.6	1	0.4	F.4,F.5
F.7	Top up hydraulic reservoirs if necessary	0.50	0.6	0.7	1	0.7	F.5
F.8	Remove warning notices	0.33	0.2	0.2	1	0.3	F.5
F.9	Close access doors, remove access platforms and safety barriers	1.00	0.5	0.5	3	0.5	F.6

10.2. Temporal Parameters

Some of the agent properties needed additional assumptions for time during implementation. For the social influence properties, it needed to be estimated how fast mechanics adopt others' opinions in aircraft maintenance teams. It was observed that with a time step of 0.01 the efforts of agents converged after about 10 days of full-time collaborative work. In real maintenance practises, however, personal aspects, such as fatigue, or environmental aspects, such as lacking tools, could also influence mechanics' effort and motivation. Considering only social influences, two weeks of intense team work were believed to accurately represent the creation of team norms. The time step of 0.01 was also introduced to the team lead effort change as well as the theory of mind effort change properties. For the theory of mind properties an additional factor of 1/4 was introduced. This factor represents the average power of one team member on the agent. The impact of an entire team at every time step was observed to be too large compared to the social influence properties.

A similar estimation needed to be performed for agents' skills. The time step for skill level development was also assumed to be 0.01. If agents execute tasks with a higher required skill level for 5 days and they have a high mastery goal, their skill level will increase with 0.1. This would mean that if an agent has a skill level of 0, it could in theory be completely experienced after 10 weeks. This would however not be possible in the real world. This research only aims to represent small skill differences during 3 days of work, rather than providing a model of skill development over longer time periods. None of the mechanics in real aircraft maintenance practises is constantly executing tasks above its skill level for 10 weeks. Moreover, mechanics' cognitive load would not permit long working hours on difficult tasks.

10.3. Statistical Evaluation

This section elaborates on two aspects of the statistical evaluation of the performed simulations. First, an overview of the evaluation of the number of Monte Carlo runs has been presented. The next section describes additional information on the statistical A-test that could be helpful for understanding the presented statistical results.

10.3.1. Coefficient of Variation

All simulations have been evaluated on the stability of their coefficient of variation for all performance indicators. The coefficient of variation evaluation is common for models without normally distributed outcomes. It is calculated for every KPI according to Equation 10.2, where μ is the KPI's mean value and σ the KPI's standard deviation.

$$c_v = \frac{\sigma(kpi)}{\mu(kpi)} \tag{10.2}$$

Figures 10.1, 10.2, 10.3, 10.4 and 10.5 present the coefficient of variation for the SC-IND-TL simulation. For all simulations and for all KPIs the variation in c_v was smaller than 0.01 after 200 runs. It was therefore concluded that the results were stable enough after 200 runs for the purpose of this research. In the multiple shifts simulation c_v was already within this range after 45 runs.

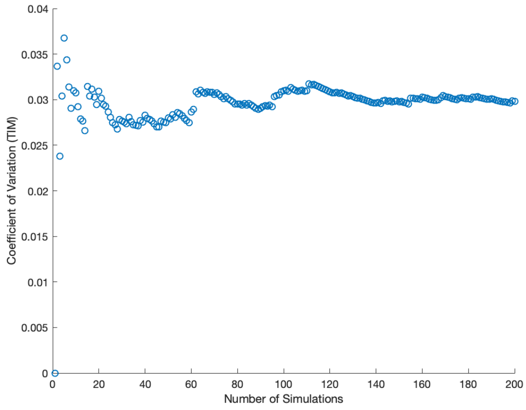


Figure 10.1: SC-IND-TL: Coefficient of variation TIM

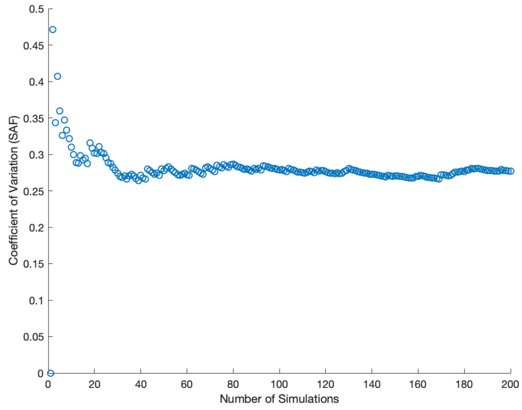


Figure 10.2: SC-IND-TL: Coefficient of variation SAF

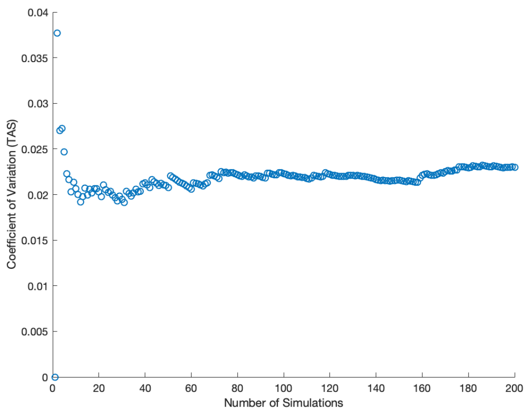


Figure 10.3: SC-IND-TL: Coefficient of variation TAS

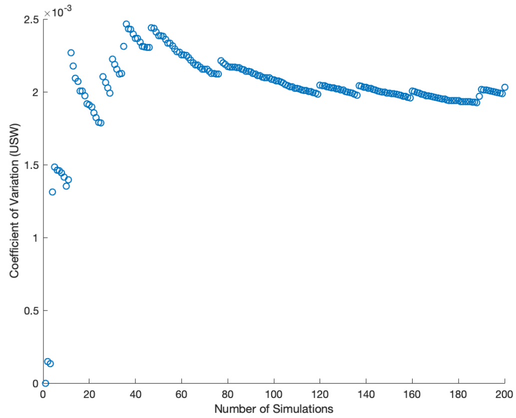


Figure 10.4: SC-IND-TL: Coefficient of variation USW

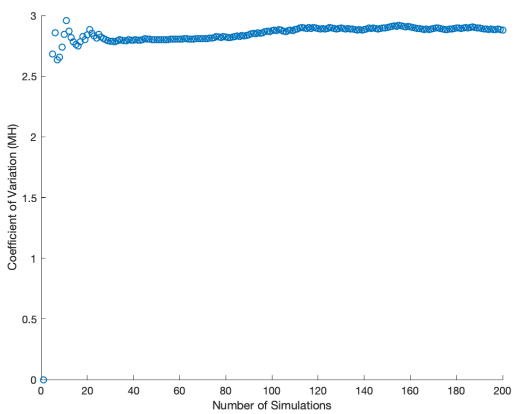


Figure 10.5: SC-IND-TL: Coefficient of variation Δ MH

10.3.2. Vargha-Delaney A-test

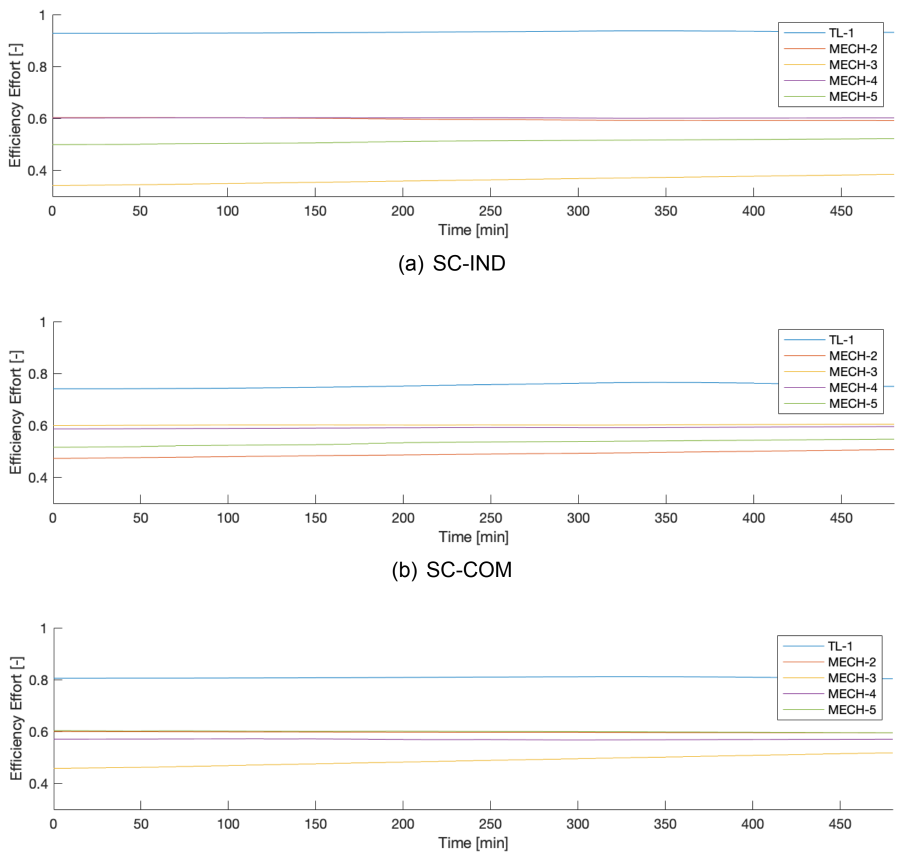
Since the Vargha-Delaney A-test is relatively new, this subsection briefly explains how to calculate and evaluate this statistic. The calculation of the A-test variable can be found in Equation 10.3 [286]. This variable compares the results of algorithm 1 and 2. R_1 is the ranksum of the two data samples, as in the Mann-Whitney-Wilcoxon test. m is the size of data set 1 and n the size of data set 2.

$$A_{12} = \frac{\frac{R_1}{m} - \frac{m+1}{2}}{n} \tag{10.3}$$

The result is a variable between 0 and 1, which represents the probability that an observation from the first data set is higher than an observation from the second data set [286]. If the A-test value is 0.5, the medians of the data sets are exactly equal. If the A-test value is either 0 or 1, there is no similarity between the data sets. Guidelines are that values between 0.51-0.56 indicate a very small difference, values between 0.56-0.71 a medium difference and values over 0.71 a large difference [287]. If one assumes that a larger value is better, the results are in favor of the first data set. Values below 0.5 then indicate a beneficial difference for the second data set. Values between 0.44-0.49 indicate a small difference, between 0.31-0.44 a medium difference and values below 0.31 a large difference.

10.4. Additional Results

The presented results in this section illustrate the observed phenomena that have been described in the scientific paper. Figure 10.6 presents the efficiency efforts of all agents for the voting protocol simulations. It shows that the social and compliant team's efficiency efforts have converged more than for the independent team. Moreover, the agent with a low efficiency effort is still converging towards the other agents faster within the social team than for the other teams.



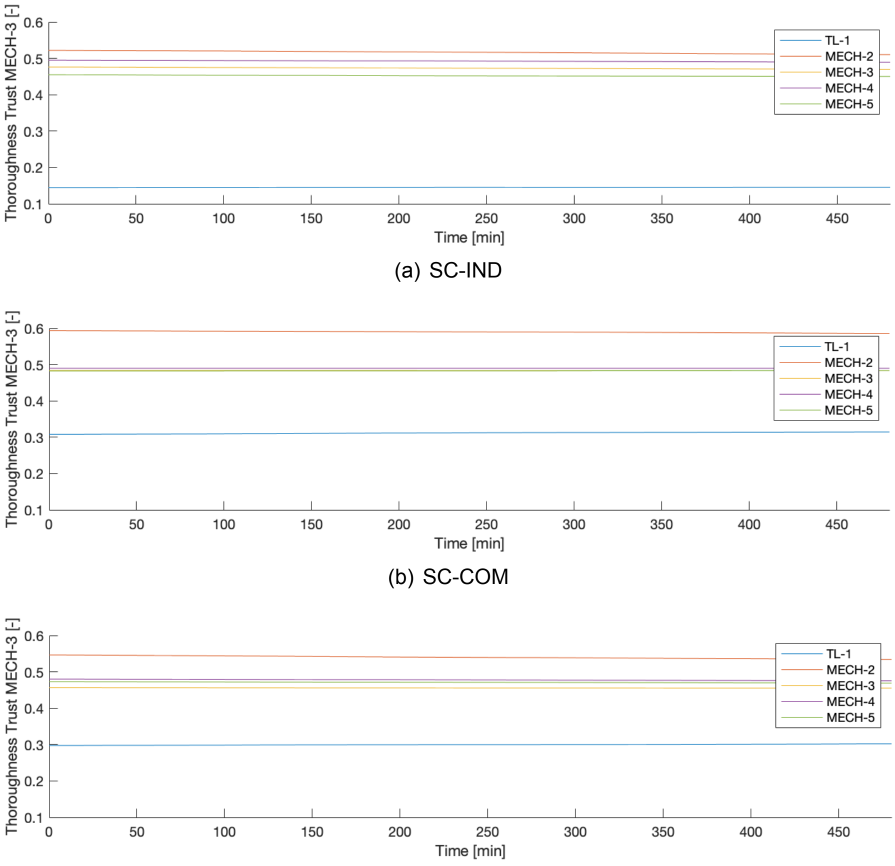
(a) SC-IND

(b) SC-COM

(c) SC-SOC

Figure 10.6: Efficiency effort for voting simulations

Figure 10.7 shows MECH-3's thoroughness trust in other agents for the mediated feedback protocol simulations. These figures show that the compliant and social teams have more shared trust beliefs than the independent teams, which can be derived from the smaller difference between the maximum and minimum trust values. Moreover, the trust levels in these graphs look constant. The trust values vary so little that it cannot be observed in these graphs. The high number of impressions during initialization makes the new impressions almost negligible.



(a) SC-IND

(b) SC-COM

(c) SC-SOC

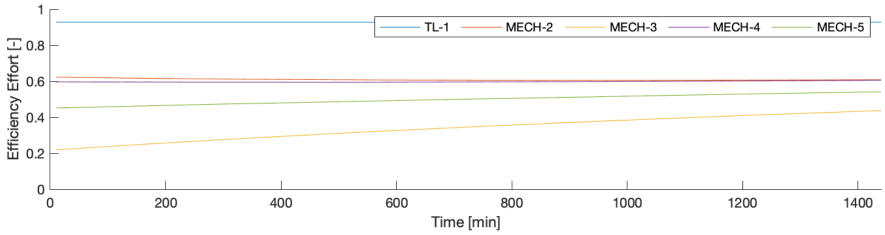
Figure 10.7: Thoroughness trust MECH-3 for mediated feedback simulations

10.5. Initialization

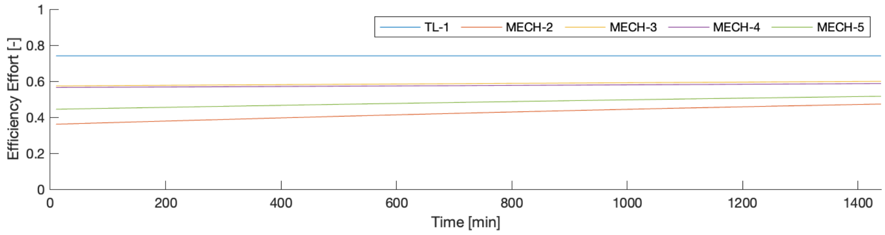
In this section the initialization graphs for thoroughness effort, efficiency effort as well as thoroughness and efficiency trust are presented. After 3 days of interaction, 1440 minutes, the task allocation starts. All simulations have been initialized for three shifts of constant encounters every 10 minutes. It can be seen that the efforts and trust values have converged, but still deviate. The mechanics are not only acting according to social norms, but also still act in line with their personal goals.

For the scenario with multiple shifts (SC-SHIFTS), initialization has been performed differently due to time constraints. The introduced time step for internalizing another person's effort has been increased by a factor of 3. The initialization has therefore been performed for only 480 minutes instead of 1440. The introduced time step creates slightly different, but similar dynamics as in the other scenarios.

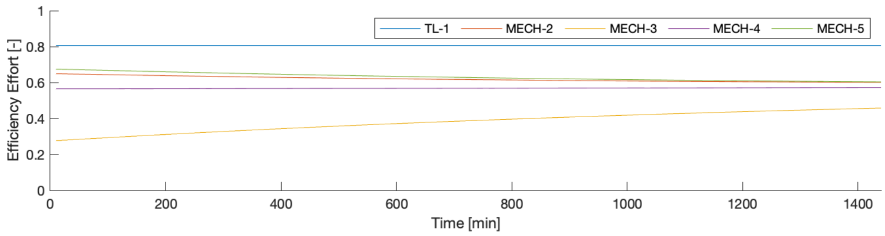
It can be observed that there is a gap in trust values for the scenarios involving new team members. It differed for every simulation run at which time point agents would encounter a newly introduced agent. This resulted in inaccurate average trust values in these figures. It was therefore decided to leave that part out of the trust graphs and represent the trust values only when stable average trust values were formed for all simulation runs.



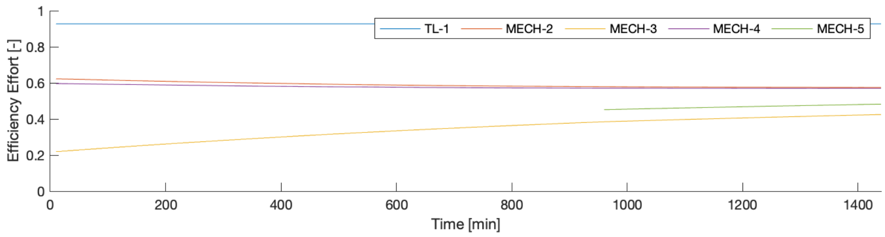
(a) SC-IND



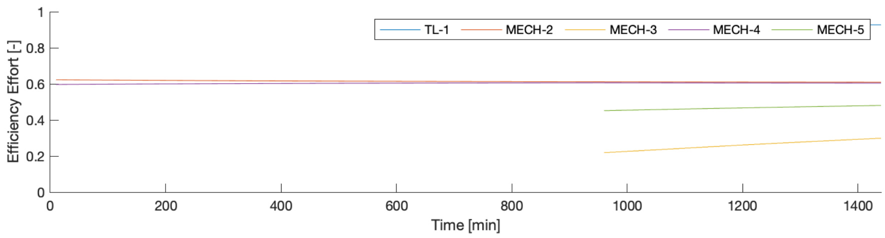
(b) SC-COM



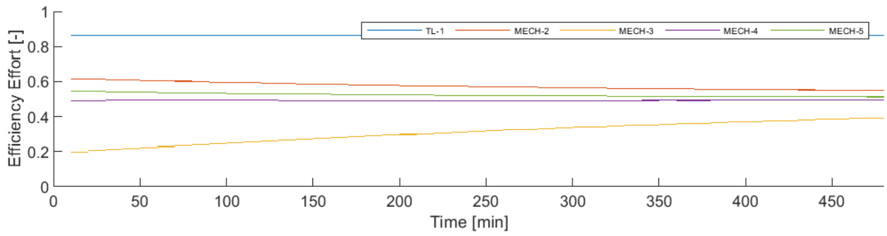
(c) SC-SOC



(d) SC-NEW-1

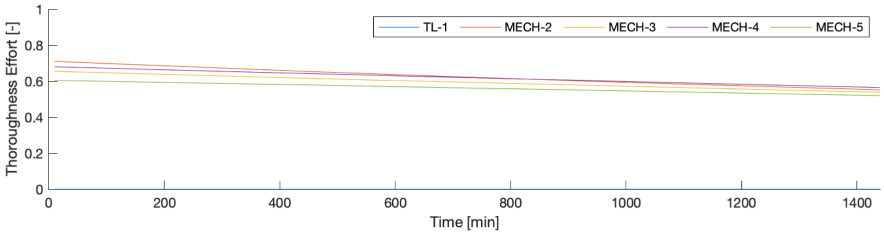


(e) SC-NEW-3

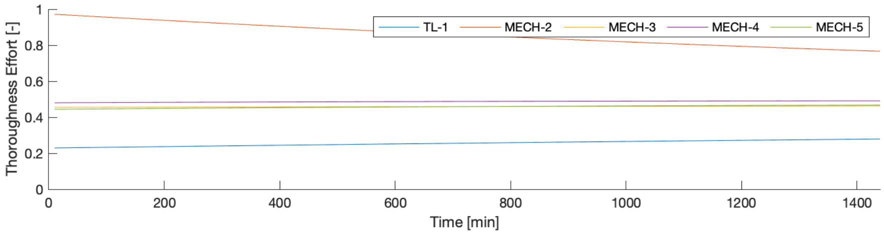


(f) SC-SHIFTS

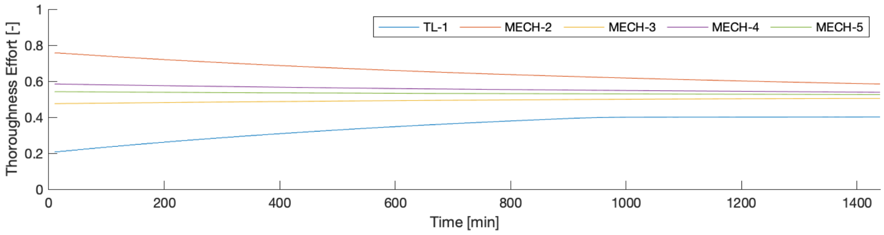
Figure 10.8: Efficiency effort initialization



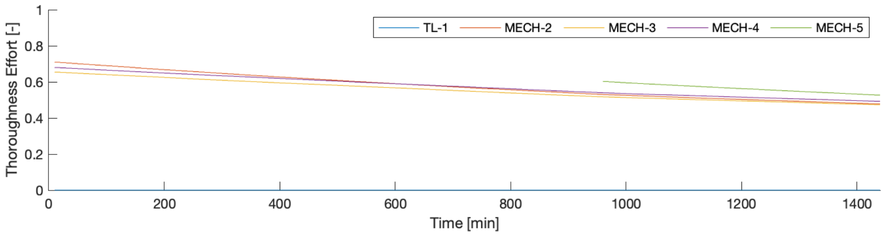
(a) SC-IND



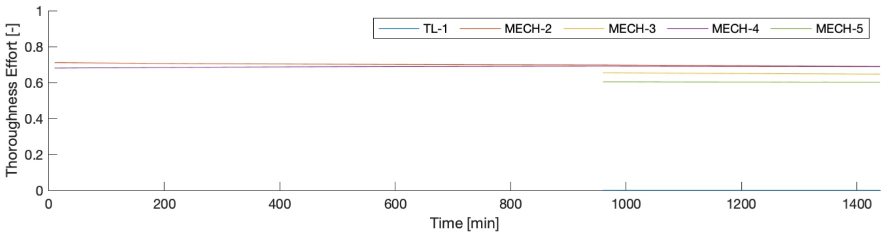
(b) SC-COM



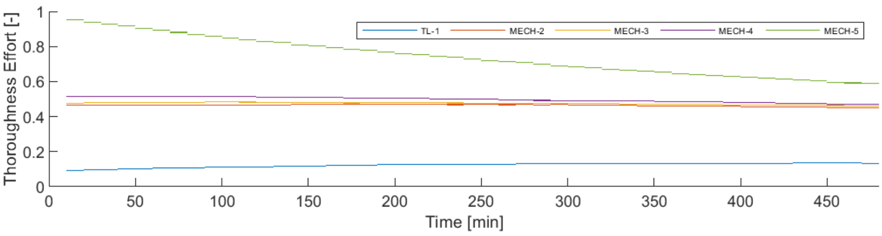
(c) SC-SOC



(d) SC-NEW-1

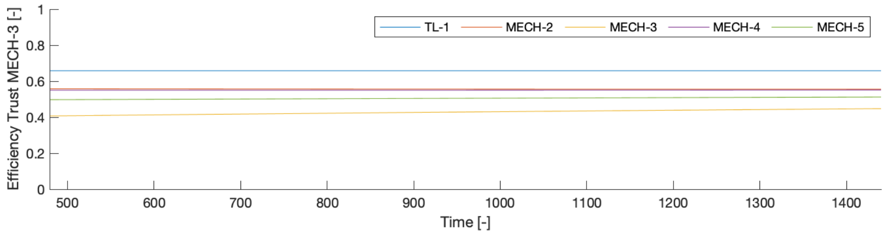


(e) SC-NEW-3

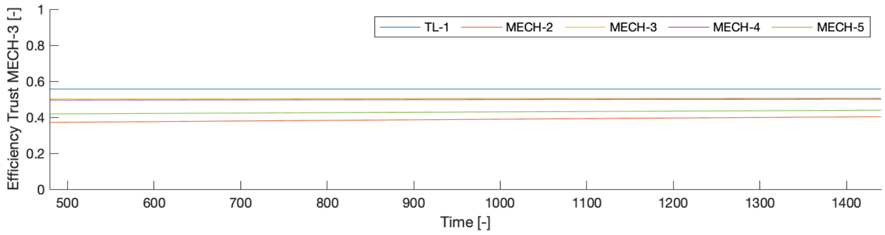


(f) SC-SHIFTS

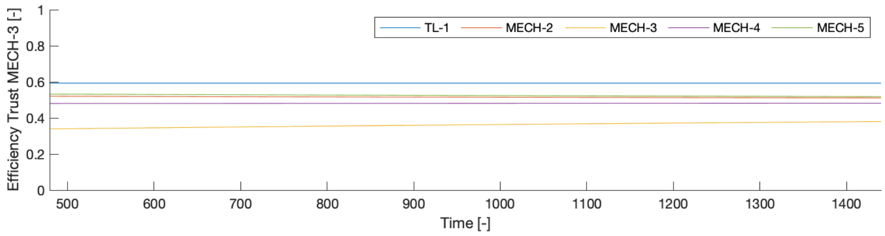
Figure 10.9: Thoroughness effort initialization



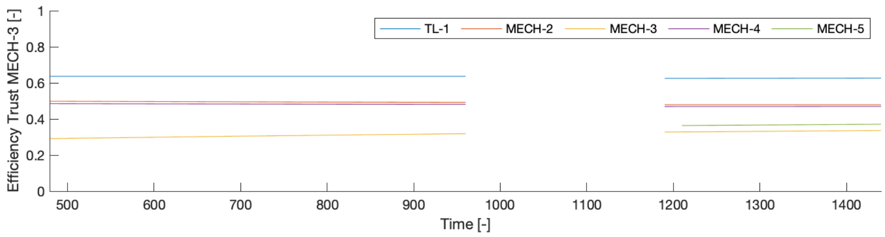
(a) SC-IND



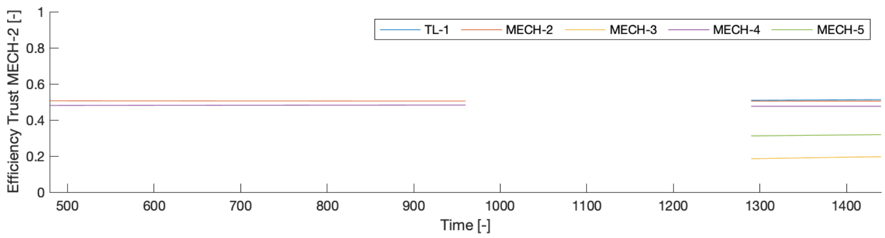
(b) SC-COM



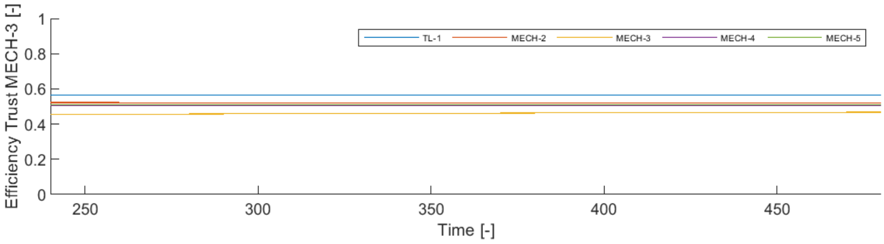
(c) SC-SOC



(d) SC-NEW-1

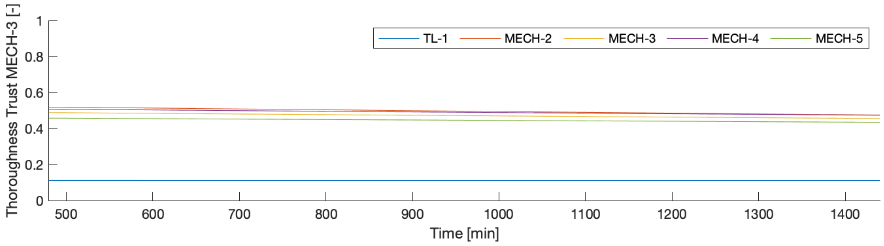


(e) SC-NEW-3

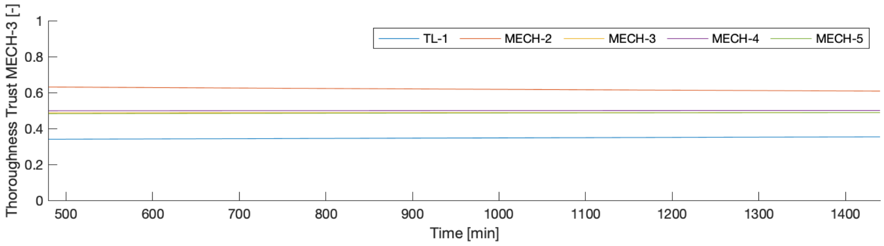


(f) SC-SHIFTS

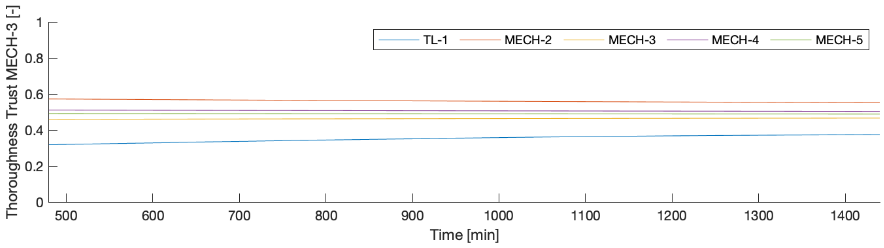
Figure 10.10: Efficiency trust initialization



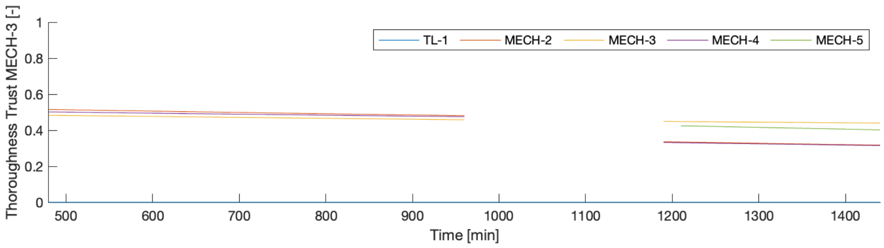
(a) SC-IND



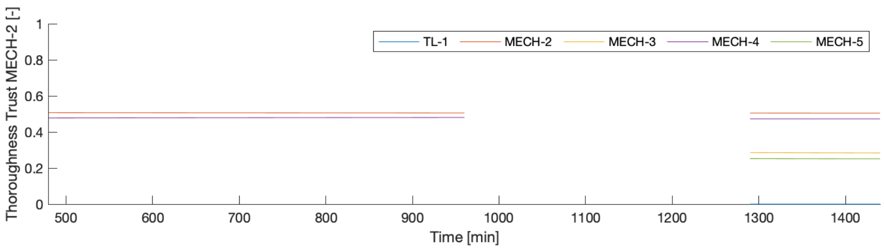
(b) SC-COM



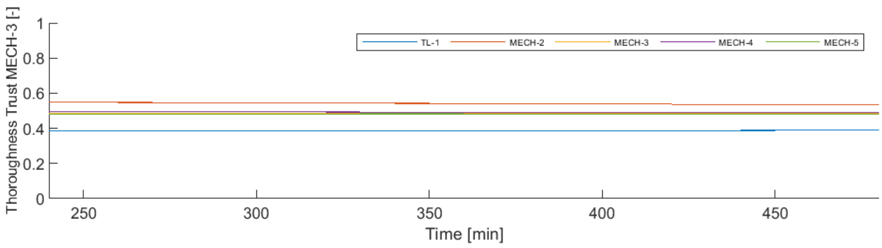
(c) SC-SOC



(d) SC-NEW-1



(e) SC-NEW-3



(f) SC-SHIFTS

Figure 10.11: Thoroughness trust initialization

11 Sensitivity Analysis

A sensitivity analysis has been performed to examine the model's validity and evaluate the robustness of the observed emergent properties. The large amount of variables in the model made global sensitivity analysis impossible within the available time period. That is why a one-at-a-time (OAT) local sensitivity analysis was performed. Yet, the number of variables was too large to evaluate all of them. It was observed during the analysis of the results that the team lead's internal goals significantly impacted the simulation results. That is why the sensitivity of its three competence goals: efficiency goal, mastery goal and thoroughness goal, has been evaluated.

The following changes have been made to these variables for analyzing sensitivity. For the efficiency and mastery goal, which were initially high, it was investigated what the effect on the results was if one of these goals would be low. To limit the number of runs, the variables have been simulated for the median of the variable range, in this case 0.3. Furthermore, a higher thoroughness goal could influence the model outcomes significantly. A high efficiency goal and a high thoroughness goal would in the real world violate the efficiency-thoroughness trade-off. So, the team lead's thoroughness goal was simulated for the median of the medium interval, which is 0.6.

The next sections evaluate the results of these three variations for the nine main simulations. Due to time constraints the simulations for sensitivity analysis were performed for 30 runs. It was observed that for most simulations the coefficient of variation was starting to stabilize. It should be kept in mind, however, that the results for 200 simulation runs could deviate a little from the ones provided below. Only significant differences will therefore be discussed.

11.1. Efficiency Goal Sensitivity

The summary statistics for the simulations with the team lead's low efficiency goal can be found in Table 11.1. These values show that, as expected, both the total execution time (TIM) and absolute execution time (TAS) are higher for most simulations. Only the mediated feedback simulation for social teams has lower TIM, but higher TAS. This difference is however not statistically significant.

The team lead's low efficiency goal decreases the efficiency effort of the other mechanics. Only the independent team lead decision-making scenario could finish all tasks in time. Social influences increase in the compliant and social teams and therefore generally increase task execution time. That is why Δ MH has also increased significantly for all simulations. SAF decreased in most simulations, since more decisions are made in favor of thoroughness if the efficiency goal is lower.

It is rather surprising that the voting simulations have a significantly higher execution time than the team lead decision-making simulations. One could expect that the individual beliefs of all other mechanics would make up for the team lead's low efficiency goal. But what we observe here, is a characteristic of the wisdom of crowds theory. The diversity in initial beliefs and preferences has decreased in these simulations with respect to the model results. This can also be observed in the higher USW values. Moreover, the high standard deviation for execution time shows that these biases can either highly increase or highly decrease the team's performance. On average, the lack of diversity causes collective decisions to be worse than individual decision-making.

The mediated feedback execution time for the independent scenario is higher than for the other two scenarios, which is the opposite of our previous results. The absolute task execution time, however, is still lowest. Moreover, the number of safety incidents is significantly lower. The decision has therefore been made in favor of absolute task execution time and safety incidents, neglecting coordination.

Table 11.1: Summary statistics for $goal_{tl}(eff) = 0.3$

	TIM [min]		SAF [-]		TAS [min]		USW [-]		Δ MH [-]		ALL [-]	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
SC-IND-TL	471.0	13.98	2.930	1.818	1762	46.68	4.966	0.006	0.497	0.051	0.167	0.379
SC-COM-TL	490.1	10.81	4.933	1.874	1857	44.13	4.916	0.010	0.560	0.039	0.000	0.000
SC-SOC-TL	481.0	19.54	3.533	1.737	1735	45.47	4.997	0.000	0.485	0.043	0.000	0.000
SC-IND-VO	547.6	62.52	3.133	1.548	1726	41.13	4.982	0.002	0.420	0.036	0.000	0.000
SC-COM-VO	529.6	73.51	4.267	2.333	1766	128.1	4.983	0.004	0.486	0.129	0.000	0.000
SC-SOC-VO	542.7	68.24	3.833	1.724	1757	54.46	4.996	0.001	0.484	0.047	0.000	0.000
SC-IND-MF	541.7	45.57	3.567	1.330	1732	60.61	4.983	0.007	0.410	0.075	0.400	0.498
SC-COM-MF	514.7	20.13	4.300	1.896	1864	60.27	4.977	0.010	0.560	0.041	0.600	0.498
SC-SOC-MF	492.7	18.74	3.600	1.850	1763	64.22	4.995	0.002	0.467	0.062	0.500	0.509

11.2. Mastery Goal Sensitivity

The sensitivity summary statistics of the simulations with the team lead's mastery goal of 0.3 are presented in Table 11.2. It can be observed that in most cases TAS is within the same range as for the presented results. The agents will generally make more decisions in favor of efficiency and thoroughness, rather than skill. This however results in more or less the same outcomes in terms of absolute execution time. The lower TAS for the compliant team lead decision-making simulation can be attributed to the increased influence of its high efficiency goal in its decision-making.

The higher TAS for the social mediated feedback scenario could be attributed to the extremely low number of safety incidents. This increases the task execution time significantly, which can also be seen in the high deviation of man-hours. Both TIM and SAF have been changed for the mediated feedback protocol simulations, more than for the other protocols. It could be the case that the team lead's high mastery goal was constraining the mediator's solution space.

Table 11.2: Summary statistics for $goal_{tl}(mas) = 0.3$

	TIM [min]		SAF [-]		TAS [min]		USW [-]		Δ MH [-]		ALL [-]	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
SC-IND-TL	432.0	14.48	6.200	1.972	1503	44.56	4.971	0.003	0.208	0.037	0.400	0.498
SC-COM-TL	422.7	19.64	4.966	2.025	1440	58.43	4.972	0.003	0.174	0.047	0.000	0.000
SC-SOC-TL	449.0	13.88	4.900	2.617	1520	34.04	4.991	0.002	0.222	0.027	0.000	0.000
SC-IND-VO	434.3	18.51	5.433	2.046	1480	34.09	4.996	0.002	0.170	0.021	0.000	0.000
SC-COM-VO	587.3	52.06	3.600	1.500	1475	29.44	4.982	0.002	0.244	0.027	0.000	0.000
SC-SOC-VO	437.3	29.53	7.700	2.136	1475	35.89	4.998	0.001	0.158	0.027	0.000	0.000
SC-IND-MF	537.3	80.00	2.670	1.446	1401	73.20	4.983	0.007	0.162	0.084	0.167	0.380
SC-COM-MF	461.7	62.37	6.200	1.518	1468	86.90	4.994	0.005	0.192	0.073	0.067	0.254
SC-SOC-MF	488.0	29.52	1.033	0.964	1756	28.34	4.988	0.006	0.501	0.027	0.133	0.346

SAF has decreased for most simulations, which is caused by the team lead's higher relative weight for thoroughness. Again, for the social and compliant teams of the voting protocol, it was found that the less divergent preference profiles result in deterioration of the decision outcome, either in terms of total execution time or safety incidents.

11.3. Thoroughness Goal Sensitivity

The summary statistics for the simulations with the team lead's thoroughness goal of 0.6 can be found in Table 11.3. Most of these simulations provided faster task execution and less safety incidents. It can be concluded that the team lead's low thoroughness goal influences the model outcome significantly.

Team lead decision-making performs generally better than voting and mediated feedback with a higher thoroughness goal for the team lead. The team lead is in these simulations less biased towards efficiency than in the case study. It therefore provides more favorable decision-making outcomes. In terms of absolute task execution time, the voting scenario still presents the best performance and the best mechanic-task fit. The team lead is still better at coordinating tasks rather than individual task assignment, due to its high experienced time pressure and efficiency goal.

Table 11.3: Summary statistics for $goal_{tl}(tho) = 0.6$

	TIM [min]		SAF [-]		TAS [min]		USW [-]		Δ MH [-]		ALL [-]	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
SC-IND-TL	420.7	25.86	2.133	1.225	1446	73.32	4.981	0.010	0.177	0.055	0.000	0.000
SC-COM-TL	407.0	18.96	2.000	1.339	1385	42.32	4.988	0.007	0.120	0.035	0.000	0.000
SC-SOC-TL	424.3	27.25	1.633	1.402	1441	90.67	4.997	0.002	0.174	0.088	0.000	0.000
SC-IND-VO	477.3	54.07	2.200	1.243	1435	39.98	4.987	0.001	0.146	0.029	0.000	0.000
SC-COM-VO	480.3	62.39	1.733	1.112	1430	25.53	4.990	0.003	0.173	0.026	0.000	0.000
SC-SOC-VO	462.0	43.26	2.200	1.518	1358	40.24	5.000	0.001	0.072	0.035	0.000	0.000
SC-IND-MF	476.3	59.16	1.933	1.285	1494	69.31	4.969	0.011	0.239	0.055	0.400	0.498
SC-COM-MF	452.0	70.04	2.467	1.383	1419	39.51	4.987	0.003	0.177	0.041	0.367	0.490
SC-SOC-MF	456.7	63.15	1.600	1.303	1462	105.4	4.986	0.007	0.199	0.121	0.200	0.407

11.4. Sensitivity Analysis Conclusion

Several conclusions can be drawn on the sensitivity of our model. First of all, it can be generally concluded that the model output is sensitive to the team lead's internal goals for competence. A low efficiency goal resulted for all simulations in significantly longer task execution time. The social and compliant team's execution time decreased more than for independent teams. The model has shown to be less sensitive to the team lead's mastery goal. A higher thoroughness goal made the team lead's decisions significantly better in terms of total execution time. It was found that for most simulations, the introduction of more similar preference profiles within the team deteriorated the voting task execution outcome. But with variations in mastery and thoroughness goals, the voting protocol still showed the best performance in mechanic-task fit. For efficiency, these results had not yet been stable enough to point out any differences. The mediated feedback protocol showed to be less competent in coordination between tasks with the introduced variations. The team lead decision-making provided in most cases the best results in terms of total execution time and safety, due to its better coordination performance.

12 Recommendations for Future Work

The main recommendations for future work are the following:

More extensive sensitivity analysis - First of all, more extensive analysis of the influence of initial values for parameters should be performed. It was observed that the initial parameters for the team lead's goals could improve or deteriorate task allocation outcomes. It should be investigated whether initial values for other agent's goals, power influence parameters or time steps for experienced time pressure, skills and theory of mind properties impact the task allocation outcomes.

Different types of motivation within a team - Other simulations could evaluate what the impact would be of different types of agent motivation within a team. For example, a team can have one independent agent, two compliant agents and two socially oriented agents. The interactions between these agents could perhaps lead to different emergent properties.

Social influence in wisdom of crowds - This research has shown that the emergent properties arising within an aircraft maintenance team are in line with the wisdom of crowds theory. It was observed that in the presented case, social influences increased the team's decision-making abilities. Research has shown that this is true for preference profiles relatively far from each other. No explanation or reason for this phenomenon has however been presented and further research could focus on the mechanisms underlying social influences within the wisdom of crowds theory.

Experimental validation - The model can be validated by setting up an experimental study that simulates the task execution process and evaluates the performance of different task allocation mechanisms. Mechanics' basic needs derived from Self-Determination Theory could be estimated using questionnaires. Other experimental validation studies could deduct preference profiles on task allocation from mechanics, using for example Discrete Choice Analysis [288].

Design of a specific task allocation automated negotiation protocol - As mentioned before, the mediated feedback protocol was not performing as expected. It was recommended to design a mediator based task allocation automated negotiation protocol. The mediator should therefore have enhanced coordination properties to include the constraint that only one mechanic can perform a task package and all task packages need to be performed. Moreover, it could be investigated if this mediator could also consider precedence constraints between tasks. If that is the case, the protocol could allocate tasks rather than task packages. Agents could then also swap tasks during task execution, rather than fixed moments in time for re-allocation of complete packages. Moreover, this design could include incentives for truthful bidding in the mediated feedback protocol.

Integrative agents for task allocation - The automated negotiation method and voting protocol could be included into an integrative agent model. An integrative agent is an agent reflecting the preferences and behavior of one real mechanic. Mechanics could provide feedback to their integrative agents on their preferences for allocation options. The integrative agents would negotiate or vote on a task allocation for their mechanic. The integrative agents can learn from the mechanic's input and eventually make decisions automatically. This could make collaborative task allocation faster eventually. Moreover, it should be investigated whether these integrative agents could monitor cognitive load and fatigue of their mechanics. The agents could then incorporate the current cognitive state of a mechanic in their decision-making as well.

Include more incentives - The proposed model already presented incentives for truthful reporting. Incentives for participation in the decision-making process are not included. It should be investigated if that is necessary, given some aircraft maintenance teams are socially oriented and are driven by a common goal. But if necessary, the model should include participation incentives.

All agents evaluate the task execution progress - In the current model only the team lead has the available knowledge about the task execution progress. This was observed to create relatively stable experienced time pressure beliefs for all mechanic agents. The model should therefore be extended such that all agents know the current state of the task execution. It is expected that this would make the model's coordination properties more accurate.

Uncertain and improved task demands - This model assumes that the task demands and times are known and the same for all agents. Mechanics reported that some people know better than others how long a task takes. Uncertainty about these variables should therefore be investigated. Moreover, estimated task time should be integrated in the agents' decision-making models for efficiency. At the moment, the efficiency requirement is deduced from the number of dependent tasks, but introducing the length of a task is expected to increase coordination performance. Moreover, the assumption that at every time point an agent has a probability of committing a safety incident should be removed. Rather, all tasks, irrespective of task length, should have the same probability on a safety incident.

Extended theory of mind properties - The agents' theory of mind properties were not found to be driving the model outcomes in any of the simulations. This is caused by the model assumption that agents aim for a reputation in line with their efforts. Mechanics could, however, aim for a higher reputation than their current effort or could aim for a specific reputation to avoid getting assigned certain tasks. The theory of mind properties should therefore be extended to incorporate other cognitive aspects of people's desire for specific reputations.

Social or personal preferences - This model has not considered personal preferences for certain tasks or social preferences for working with specific team members. Further research could extend the current model with personal preferences. In that case, an incentive system could be created to ensure that mechanics still decide in line with the team goals rather than only their personal interests.

Bibliography

[1] P. Davidsson. Agent based social simulation: A computer science view. *Journal of Artificial Societies and Social Simulation*, 5, 2002.

[2] A. van der Mee, N.M. Mogles, and J. Treur. *An Integrative Agent Model for Adaptive Human-Aware Presentation of Information during Demanding Tasks*. Springer, Berlin, Heidelberg, 2009.

[3] A. Sharpanskykh. Powerpoint slides - lecture 1: Introduction to agents and multi-agent systems. specification of multi-agent systems. emergence. 2018.

[4] G.E. Kersten and H. Lai. Negotiation support and e-negotiation systems: An overview. *Group Decision and Negotiation*, 16:553–586, 2007.

[5] E.M. Rogers. *Diffusion of Innovations*. The Free Press, New York, NY, 1995.

[6] Deloitte. Deloitte digital business obstacle: Digitization. Retrieved July 11th 2019, from `https://www2.deloitte.com/lu/en/pages/technology/articles/deloitte-digital-business-obstacle-organization-digitization.html`, 2019.

[7] Strategy&. The digitization megatrend. Retrieved July 11th 2019, from `https://www.strategyand.pwc.com/digitization#VisualTabs5`, 2019.

[8] Ernst&Young. The digitisation of everything. Retrieved July 11th 2019, from `https://www.ey.com/Publication/vwLUAssets/The_digitisation_of_everything_-_How_organisations_must_adapt_to_changing_consumer_behaviour/%24file/EY_Digitisation_of_everything.pdf`, 2019.

[9] McKinsey&Company. Unlocking success in digital transformations. Retrieved July 11th 2019, from `https://www.mckinsey.com/business-functions/organization/our-insights/unlocking-success-in-digital-transformations`, 2019.

[10] C.R. Hargraves and S.W. Paris. Direct trajectory optimization using nonlinear programming and collocation. *Journal of Guidance Control and Dynamics*, 10, 1986.

[11] T. Fiig, K. Isler, C. Hopperstad, and P. Belobaba. Optimization of mixed fare structures: Theory and applications. *Journal of Revenue and Pricing Management*, 9:152–170, 2010.

[12] M. Bazargan. *Airline Operations and Scheduling*. Routledge, 2010.

[13] G.-F. Deng and W.-T. Lin. Ant colony optimization-based algorithm for airline crew scheduling problem. *Expert Systems with Applications*, 38:5787–5793, 2011.

[14] D. Dinis and A. P. Barbosa-Póvoa. *On the Optimization of Aircraft Maintenance Management*. Springer, Switzerland, 2015.

[15] G. Ropohl. Philosophy of socio-technical systems. *Research in Philosophy and Technology*, 4:186–194, 1999.

[16] M.S. Poole and G. DeSanctis. Understanding the use of group decision support systems: The theory of adaptive structuration. In J. Fulk and C. Steinfield, editors, *Organizations and Communication Technology*. Sage Publications, Thousand Oaks, California, 1990.

[17] de Volkskrant. Opinieblog - 'we kijken met oude ideeën naar de nieuwe digitale samenleving'. Retrieved July 11th 2019, from `https://www.volkskrant.nl/columns-opinie/opinieblog-we-kijken-met-oude-ideeen-naar-de-nieuwe-digitale-samenleving~b4b2629a/`, 2019.

[18] A. Miles. Complexity in medicine and healthcare: people and systems, theory and practice. *Journal of Evaluation in Clinical Practice*, 15, 2009.

[19] M. M. Benham-Hutchins and T. R. Clancy. Social networks as embedded complex adaptive systems. *The Journal of Nursing Administration*, 40:352–360, 2010.

[20] S. Fatima, S. Kraus, and M. Wooldridge. *Principles of Automated Negotiation*. Cambridge University Press, Cambridge, UK, 2014.

[21] Y. Shoham and K. Leyton-Brown. *MultiAgent Systems: Algorithmic, Game-Theoretic, and Logical Foundations*. Cambridge University Press;, 2008.

[22] D. Helbing and S. Balietti. *How to Do Agent-Based Simulations in the Future: From Modeling Social Mechanisms to Emergent Phenomena and Interactive Systems Design*. Springer-Verlag, Berlin Heidelberg, 2012.

[23] L. Pintelon and A. Parodi-Herz. *Maintenance: An Evolutionary Perspective*. Springer, London, 2008.

[24] P.P.M. Callewaert. Integrating maintenance work progress monitoring into aircraft maintenance planning decision support. Master's thesis, Delft University of Technology, 2016.

[25] R. Dekker. Applications of maintenance optimization models: a review and analysis. *Reliability Engineering and System Safety*, 51:229–240, 1996.

[26] N. M. Paz and W. Leigh. Maintenance scheduling: Issues, results and research needs. *International Journal of Operations Production Management*, 14:47–69, 1994.

[27] D.L. Coolen. Maintenance planning scheduling for aircraft line maintenance. Master's thesis, Delft University of Technology, 2018.

[28] P. Fattahi, M.S. Mehrabad, and F. Jolai. Mathematical modeling and heuristic approaches to flexible job shop scheduling problems. *Journal of Intelligent Manufacturing*, 18:331–342, 2007.

[29] R. Kolisch. Serial and parallel resource-constrained project scheduling methods revisited: Theory and computation. *European Journal of Operational Research*, 90:320–333, 1996.

[30] K. Zoethout. *Self-organising processes of task allocation: a multi-agent simulation study*. PhD thesis, University of Groningen, 2006.

[31] S.A. Suarez Baron. *Dynamic Task Allocation and Coordination in Cooperative Multi-agent Environments*. PhD thesis, University of Girona, 2010.

[32] A. Cheung, W.H. Ip, and D. Lu. Expert system for aircraft maintenance services industry. *Journal of Quality in Maintenance*, 11:348–358, 2005.

[33] J. Beliën, B. Cardoen, and E. Demeulemeester. Improving workforce scheduling of aircraft line maintenance at sabena technics. *Journal on Applied Analytics*, 42:352–364, 2012.

[34] H.K. Alfares. Aircraft maintenance workforce scheduling:a case study. *Journal of Quality in Maintenance Engineering*, 5:78–89, 1999.

[35] G. Quan, G.W. Greenwood, D. Liu, and S. Hu. Searching for multiobjective preventive maintenance schedules: combining preferences with evolutionary algorithms. *European Journal of Operational Research*, 177: 1969–1984, 2007.

[36] D. Bertsimas, S. Gupta, and G. Lulli. Dynamic resource allocation: a flexible and tractable modeling framework. *European Journal of Operational Research*, 236:14–26, 2014.

[37] J. Brimberg and W.J. Hurley. Scheduling workers in constricted area. *Naval Research Logistics*, 43:143–149, 1996.

[38] ICAO. Icao annex 1: The convention on international civil aviation. Retrieved July 12th, 2019 from `https://store.icao.int/icao-annex-1`, 2019.

[39] EASA. Which are the part-66 licences? Retrieved July 12th, 2019 from `https://www.easa.europa.eu/faq/19017`, 2019.

[40] D. Kumar Yadav. Licensing and recognition of the aircraft maintenance engineers - a comparative study. *Journal of Air Transport Management*, 16:272–278, 2010.

[41] J. van den Bergh, P. De Bruecker, J. Belien, and J. Peeters. Aircraft maintenance operations: state of the art. `https://core.ac.uk/download/pdf/34583783.pdf`, 2013.

[42] H. Zhaodong, C. Wenbing, X. Yiyong, and L. Rui. Optimizing human resources allocation on aircraft maintenance with predefined sequence. In *2010 International Conference on Logistics Systems and Intelligent Management (ICLSIM)*, pages 1018–1022, 2010.

[43] D.C. Dietz and M. Rosenshine. Optimal specialization of a maintenance workforce. *IEE Transactions*, 29: 423–433, 1997.

[44] C.-L. Wu. *Airline Operations and Delay Management: Insights from Airline Economics, Networks and Strategic Schedule Planning*. Taylor and Francis, London, UK, 2010.

[45] R. Dekker and P.A. Scarf. On the impact of optimisation models in maintenance decision making: the state of the art. *Reliability Engineering and System Safety*, 60:111–119, 1998.

[46] R.H. Sprague. A framework for the development of decision support systems. *MIS Quarterly*, 4:1–26, 1980.

[47] S. Ponomarev and A.E. Voronkov. Multi-agent systems and decentralized artificial superintelligence. *CoRR*, 2017.

[48] S. Kraus. Negotiation and cooperation in multi-agent environments. *Artificial Intelligence*, 94, 1998.

[49] A.H. Bond and L. Gasser. *Readings in Distributed Artificial Intelligence*. Morgan Kaufmann Publishers, San Francisco, CA, USA, 1988.

[50] A. Dorri, S. Kanhere, and R. Jurdak. Multi-agent systems: A survey. *IEEE Access*, 2018.

[51] K.P. Sycara. Multiagent systems. *AI Magazine*, 19:79–92, 1998.

[52] E. Bonabeau. Agent-based modeling: Methods and techniques for simulating human systems. In *Proceedings of the National Academy of Sciences 2002*, pages 7280–7287, May 2002.

[53] S. Franklin and A. Graesser. Is it an agent, or just a program?: A taxonomy for autonomous agents. In *Proceedings of the Third International Workshop on Agent Theories, Architectures and Languages*. Springer-Verlag, 1996.

[54] M. Wooldridge. Verifiable semantics for agent communication languages. In *Proceedings International Conference on Multi Agent Systems*, pages 349–356, Paris, France, 1998.

[55] M. Niazi and A. Hussain. Agent-based computing from multi-agent systems to agent-based models: a visual survey. *Scientometrics*, 89:479–499, 2011.

[56] H. Van Dyke Parunak, R. Savit, and R.L. Riolo. Agent-based modeling vs. equation-based modeling: a case study and users' guide. In *International Workshop on Multi-Agent-Systems and Agent-Based Simulation*, pages 10–25. Springer, 1998.

[57] F. Klugl and A.L.C. Bazzan. Agent-based modeling and simulation. *AI Magazine*, 33:29, 2012.

[58] H.F. Ahmad. Multi-agent systems: overview of a new paradigm for distributed systems. In *7th IEEE International Symposium on High Assurance Systems Engineering, 2002. Proceedings.*, pages 101–107, Oct 2002.

[59] G. Weiss. *Multiagent systems: a modern approach to distributed artificial intelligence*. The MIT Press, Cambridge, Massachusetts, 1999.

[60] T. Balke and N. Gilbert. How do agents make decisions? a survey. *Journal of Artificial Societies and Social Simulation*, 17:13, 2014.

[61] M. E. Bratman. *Intention, Plans and Practical Reason*. CSLI Publications, Stanford, California, 2014.

[62] H. Jiang, J.M. Vidal, and M.N. Huhns. Ebdi: an architecture for emotional agents. In *6th International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS 2007), Honolulu, Hawaii, USA*, 2007.

[63] J. Broersen, M. Dastani, J. Hulstijn, and L. van der Torre. Goal generation in the boid architecture. *Cognitive Science Quarterly*, 2, 2002.

[64] F. Dignum, V. Dignum, and C.M. Jonker. Towards agents for policy making. In *International Workshop on Multi-Agent Systems and Agent-Based Simulation*, pages 141–153, 2008.

[65] R. Sun. Motivational representations within a computational cognitive architecture. *Cognit*, 1:91–103, 2009.

[66] A. Sharpanskykh. *On computer-aided methods for modeling and analysis of organizations*. PhD thesis, Vrije Universiteit Amsterdam, 2008.

[67] R. Bordini, L. Dennis en B. Farwer, and M. Fisher. *Directions for Agent Model Checking*. Springer, Boston, MA, 2010.

[68] M. Dastani and JJ.C. Meyer. *Correctness of Multi-Agent Programs: A Hybrid Approach*. Springer, Boston, MA, 2010.

[69] M. van Riemsdijk, L. Aştefănoaei, and F. de Boer. *Using the Maude Term Rewriting Language for Agent Development with Formal Foundations*. Springer, Boston, MA, 2010.

[70] K.V. Hindriks, F.S. de Boer W. van der Hoek, and J.-J. Ch. Meyer. Agent programming in 3apl. *Autonomous Agents and Multi-Agent Systems*, 2:357–401, 1999.

[71] N. Alechina, M. Dastani, F. Khan, B. Logan, and J.-J.Ch. Meyer. *Using Theorem Proving to Verify Properties of Agent Programs*. Springer, Boston, MA, 2010.

[72] L. Astefanoaei and F.S. de Boer. *The Refinement of Multi-Agent Systems*. Springer, Boston, MA, 2010.

[73] S. Shapiro, Y. Lespérance, and H.J. Levesque. The cognitive agents specification language and verification environment for multiagent systems. In *Proceedings of the first international joint conference on autonomous agents and multiagent systems (AAMAS'02)*, pages 19–26, 2002.

[74] A.S. Rao. Agentspeak(l):bdi agents speak out in a logical computable language. In *Agents Breaking Away: Proceedings of the Seventh European Workshop on Modelling Autonomous Agents in a Multi-Agent World (MAAMAW'96)*, pages 42–55, 1996.

[75] A. Sharpanskykh and J. Treur. *A Temporal Trace Language for Formal Modelling and Analysis of Agent Systems*. Springer, Boston, MA, 2010.

[76] T. Bosse, C. Jonker, L. van der Meij, and J. Treur. A language and environment for analysis of dynamics by simulation. *International Journal of Artificial Intelligence Tools*, 16:435–464, 2007.

[77] S. Abar, G.K. Theodoropoulos, P. Lemarinier, and G. O'Hare. Agent based modelling and simulation tools: A review of the state-of-art software. *Computer Science Review*, 24:13–33, 2017.

[78] N. Bulling, J. Dix, and W. Jamroga. *Model Checking Logics of Strategic Ability: Complexity*. Springer, Boston, MA, 2010.

[79] K.V. Hindriks. *A Verificiation Logic for Goal Agents*. Springer, Boston, MA, 2010.

[80] J. Bentahar, J.-J.Ch. Meyer, and W. Wan. *Model Checking Agent Communication*. Springer, Boston, MA, 2010.

[81] T. Bosse, R. Duel, M. Hoogendoorn, M. Klein, R. van Lambalgen, A. van der Mee, R. Oorburg, A. Sharpanskykh, J. Treur, and M. de Vos. *A Generic Personal Assistant Agent Model for Support in Demanding Tasks*. Berlin, Heidelberg, 2009.

[82] T. Bosse and C. Gerritsen. *A Model-Based Reasoning Approach to Prevent Crime*. Berlin, Heidelberg, 2010.

[83] J. Treur. *On Human Aspects in Ambient Intelligence*. Springer, Berlin, Heidelberg, 2008.

[84] C.D. Wickens. Situation awareness and workload in aviation. *Current Directions in Psychological Sciences*, 11:128–133, 2002.

[85] R. Parasuraman and V. Riley. Humans and automation: use, misuse, disuse, abuse. *Human Factors*, 39: 230–253, 1997.

[86] Q. Zhong, X. Fan, X.Luo, and F. Toni. An explainable multi-attribute decision model based on argumentation. *Human Factors*, 117:42–61, 2019.

[87] F.K. Došilović, M. Brčić, and N. Hlupić. Explainable artificial intelligence: A survey. In *41st International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO) Opatija*, pages 210–215, 2018.

[88] J. E. Mercado, M. Rupp, J. Chen, M. Barnes, D. Barber, and K. Procci. Intelligent agent transparency in human-agent teaming for multi-uxv management. *Human Factors: The Journal of the Human Factors and Ergonomic Society*, 58:401–415, 2016.

[89] Z.C. Lipton, D.C. Kale, C. Elkan, S. Vikram R. Wetzell, J. McAuley, R.C. Wetzell, Z. Ji, B. Narayaswamy, and C.I. Wang. The mythos of model interpretabilit. *IEEE Spectrum*, 2016.

[90] S. Devin and R. Alami. An implemented theory of mind to improve human-robot shared plans execution. In *Eleventh ACM/IEEE International Conference on Human Robot Interaction*, pages 319–326, 2016.

[91] L.J. Byom and B. Mutlu. Theory of mind: mechanisms, methods and new directions. *Frontiers in Human Neuroscience*, 7:413, 2013.

[92] L. Amgoud and H. Prade. Using arguments form making and explaining decisions. *Artificial intelligence*, 173:413–436, 2009.

[93] T. Miller. Explanation in artificial intelligence: insights from the social sciences. *Artificial intelligence*, 267: 1–38, 2019.

[94] C. van Aart. *Organizational Principles for Multi-Agent Architectures*. Birkhauser Verlag, Basel, 2000.

[95] S. Kraus, O. Shehory, and G. Taase. Coalition formation with uncertain heterogeneous information. In *AAMAS '03 Proceedings of the second international joint conference on Autonomous agents and multiagent systems*, pages 1–8, 2003.

[96] X. Zheng and S. Koenig. Reaction functions for task allocation to cooperative agents. In *Proceedings of 7th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2008)*, pages 559–566, 2008.

[97] R. Davis and R.G. Smith. Negotiation as a metaphor for distributed problem solving. *Artificial Intelligence*, 20:63–109, 1983.

[98] Y. Wang, Y. Xu, and X. Zhang. Task-allocation algorithm for collaborative design based on negotiation mechanism. In *2009 13th International Conference on Computer Supported Cooperative Work in Design*, pages 102–106, 2009.

[99] H. Zhang, Y. Su, L. Peng, and D. Yao. A review of game theory applications in transportation analysis. In *International Conference on Computer and Information Application(ICCIA)*, 2010.

[100] D. Scherer dos Santos and A.L.C. Bazzan. Distributed clustering for group formation and task allocation in multiagent systems: A swarm intelligence approach. *Applied Soft Computing*, 12:2123–2131, 2012.

[101] N.K. Krothapalli. *Dynamic task allocation in multi-agent systems*. PhD thesis, University of Massachusetts at Amherst, 2003.

[102] M.N. Huhns and L.M. Stephens. Multiagent systems and societies of agents. 1999.

[103] Y. Jiang and Z. Li. Locality-sensitive task allocation and load balancing in networked multiagent systems: Talent versus centrality. *Journal of Parallel and Distributed Computation*, 71:822–836, 2011.

[104] Y. Jiang and J. Jiang. Contextual resource negotiation-based task allocation and load balancing in complex software systems. *Parallel and Distributed Systems*, pages 641–653, 2009.

[105] F. Rahimzadeh, L.M. Khanli, and F. Mahan. High reliable and efficient task allocation in networked multi-agent systems. *Autonomous Agents and Multi-Agent Systems*, 29:1023–1040, 2014.

[106] M. Beer, M. D'Inverno, M. Luck, N. Jennings, C. Preist, and M. Schroeder. Negotiation in multi-agent systems. *The Knowledge Engineering Review*, 14:285–289, 1999.

[107] H. Gimpel. *Cognitive Biases in Negotiation Processes*. Springer, Berlin, 2008.

[108] G.E. Kersten, E. Chen, D. Neumann, R. Vahidov, and C. Weinhardt. *On Comparison of Mechanisms of Economic and Social Exchanges: The Times Model*. Springer, Berlin, 2008.

[109] I. Rahwan, S.D. Ramchurn, N.R. Jennings, P. McBurney, S. Parsons, and L. Sonenberg. Argumentation-based negotiation. *The Knowledge Engineering Review*, 18:343–375, 2004.

[110] R.G. Smith. The contract net protocol: High-level communication and control in a distributed problem solver. *IEEE Transactions on Computers*, 29:1104–1113, 1980.

[111] T. Sandholm and V. Lesser. Issues in automated negotiation and electronic commerce: Extending the contract net framework. In *Proceedings of the First International Conference on Multiagent Systems ICMAS-95*, 1995.

[112] T.W. Sandholm. Contract types for satisficing task allcation: I theoretical results. *AAAI Technical Report*, 1998.

[113] M.R. Andersson and T.W. Sandholm. Contract types for satisficing task allcation: Ii experimental results. *AAAI Technical Report*, 1998.

[114] V. Conitzer. Making decisions based on the preferenes of multiple agents. *Communications of the ACM*, 53:84–94, 2010.

[115] V. Krishna. *Auction Theory*. Academic Press/Elsevier, Cambridge, Massachusetts, 2002.

[116] P.R. Milgrom and R.J. Weber. A theory of auctions and competitive bidding. *Econometrica*, 50:1089–1122, 1982.

[117] P. Winoto, G. Mccalla, and J. Vassileva. An extended alternating-offer bargaining protocol for automated negotiation in multi-agent systems. In *OTM Confederated International Conferences: On the Move to Meaningful Internet Systems*, pages 179–194, 2002.

[118] C. Tovey, M. G. Lagoudakis, S. Jain, and S. Koenig. The generation of bidding rules for auction-based robot coordination. *Multi-Robot Systems, From Swarms to Intelligence Automata Volume III*, pages 3–14, 2005.

[119] X. Zheng, C. Tovey, and R. Borie. Agent coordination with regret clearing. In *Proceedings of the Twenty-Third AAAI Conference on Artificial Intelligence*, 2008.

[120] S. Koenig, C. Tovey, X. Zheng, and I. Sungur. Sequential bundle-bid single-sale auction algorithms for decentralized control. In *IJCAI 2007, Proceedings of the 20th International Joint Conference on Artificial Intelligence, Hyderabad, India*, 2007.

[121] I. Stahl. Bargaining theory: Computer programs, 1972.

[122] A. Rubinstein. Perfect equilibrium in a bargaining model. *Econometrica*, 50:97–109, 1982.

[123] S. Kraus. *Strategic Negotiation in Multiagent Environments*. The MIT Press, Cambridge, Massachussets, 2001.

[124] M.J. Osborne and A. Rubinstein. *Bargaining and Markets*. Emerald, 1990.

[125] T. Sandholm and N. Vulkan. Bargaining with deadlines. In *AAAI'99 Proceedings of the sixteenth national conference on Artificial intelligence and the eleventh Innovative applications of artificial intelligence conference*, pages 44–51, Orlando, Florida, USA, 1999.

[126] J.K. Murnighan, A.E. Roth, and F. Schoumaker. Risk aversion in bargaining: an experimental study. *Journal of Risk and Uncertainty*, 1:101–124, 1988.

[127] J.F. Nash. The bargaining problem. *Econometrica*, 18(2):155–162, 1950.

[128] E. Kalai and M. Smorodinsky. Other solutions to nash's bargaining solution. 43:513–518, 1975.

[129] K.J. Arrow and G. Debreu. Existence of an equilibrium for a competitive economy. *Econometrica*, 22: 265–290, 1954.

[130] D.E. Campbell and J.S. Kelly. Impossibility theorems in the arrovian framework, 2002.

[131] V. Conitzer and T. Sandholm. Universal voting protocol tweaks to make manipulation hard. In *In Proceedings of the 18th International Joint Conference on Artificial Intelligence (IJCAI-03)*, 2003.

[132] E. Ephrai and J.S. Rosenschein. The clarke tax as a consensus mechanism among automated agents. In *AAAI-91 Proceedings*, 1991.

[133] O. Lev and J.S. Rosenschein. Convergence of iterative voting. In *AAMAS '12 Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems - Volume 2*, pages 611–618, 2012.

[134] R. Meir, M. Polukarov, J.S. Rosenschein, and N.R. Jennings. Convergence to equilibria in plurality voting. In *Proceedings of the Twenty-Fourth AAAI Conference on Artificial Intelligence*, pages 823–828, 2010.

[135] J. Pitt, L. Kamara, M. Sergot, and A. Artikis. *The Computer Journal*, 49:156–170, 2006.

[136] V. Conitzer. Comparing multiagent systems research in combinatorial auctions and voting. *Annals of Mathematics and Artifical Intelligence*, 58:239–259, 2010.

[137] V. Conitzer. Should social network structure be taken into account in elections? *Mathematical Social Sciences*, 64:100–102, 2012.

[138] S. Nitzan and J. Paroush. Optimal decision rules in uncertain dichtomous choice situations. *International Economic Review*, 23:289–297, 1982.

[139] J. Martin. Consuming code: Use-value, exchange value and the role of virtual goods in second life. *Journal of Virtual Worlds Research*, 1, 2008.

[140] M.J. Zimmerman and B. Bradly. Intrinsic vs. extrinsic value. Retrieved July 8th 2019, from `https://plato.stanford.edu/entries/value-intrinsic-extrinsic/`, 2019.

[141] P.N. Junankar. *Marx's economics*. Philip Allan, Oxford, 1982.

[142] I.I. Rubin. Abstract labour and value in marx's system. *Capital and Class*, 5:107–139, 1978.

[143] J. Milios. Marx's value theory revisited. a value-form approach. In *Proceedings of the Seventh International Conference in Economics*, 2003.

[144] J. Nitzan and S. Bichler. *Capital as Power: A Study of Order and Creorder*. Routlegde, 2009.

[145] E. von Bawerk. *Book III, Chapter IV: The Marginal Utility*. 1891.

[146] J. von Neumann and O. Morgenstern. *Theory of Games and Economic Behavior*. Princeton University Press, Princeton, New Jersey, 1947.

[147] B. Koszegi and M. Rabin. Mistakes in choice-based welfare analysis. *American Economic Review: Papers and Proceedings*, 97:477–481, 2007.

[148] R.T. Carson. Contigent valuation: A user's guide. *Environmental Science Technology*, 34:1413–1418, 2000.

[149] D. Kahneman and A. Tversky. Prospect theory: an analysis of decision under risk. *Econometrica*, 47: 263–292, 1979.

[150] S.S. Fatima. *Bidding Strategies for Multi-object Auctions*. Springer, Berlin, 2008.

[151] J.K. Goeree and T. Offerman. Competitive bidding in auctions with private and common values. *The Economic Journal*, 113:598–613, 2003.

[152] G. Parmigiani. *Decision Theory: Bayesian*, pages 3327–3334. 2001.

[153] R. Myerson. *Game Theory: Analysis of Conflict*. Harvard University Press, Cambridge, Massachusetts, 1991.

[154] N.R. Jennings, P. Faratin, A.R. Lomuscio, S. Parsons, M. Wooldridge, and C. Sierra. Automated negotation: Prospects, methods and challenges. *Group Decision and Negotiation*, 10:199–215, 2001.

[155] W. Guth and H. Kliemt. (un)bounded rationality in decision making and game theory - back to square one? *Games*, 1:53–65, 2010.

[156] G. Cimini and A. Sanchez. Learning dynamics explains human behaviour in prisoner's dilemma on networks. *Journal of The Royal Society Interface*, 11, 2014.

[157] J. Tillett. Bounded rationality in the iterated prisoner's dilemma. Retrieved July 25th, 2019 from: `https://www.cs.ubc.ca/~kevinlb/teaching/cs532a%20-%202004-5/Class%20projects/Jenn.pdf`, 2005.

[158] D.G. Myers. *Social psychology*. McGraw-Hill, New York, NY, 2010.

[159] P. Faratin, C. Sierra, and N. Jennings. Negotiation decision functions for autonomous agents. *Robotics and Autonomous Systems*, 24:159–182, 1998.

[160] J.R. Oliver. A machine-learning approach to automated negotiation and prospects for electronic commerce. *Journal of Management Information Systems*, 13:83–112, 1996.

[161] D. Zeng and K. Sycara. Bayesian learning in negotiation. *International Journal of Human-Computer Studies*, 48:125–141, 1998.

[162] C. Luo and S.X. Yang. A real-time cooperative sweeping strategy for multiple cleaning robots. In *Proceedings of the IEEE Internatinal Symposium on Intelligent Control Vancouver, Canada*, pages 660–665, 2002.

[163] S. Parsons and N.R. Jennings. Argumentation and multi-agent decision making. In *Proceedings of the AAAI Spring Symposium on Interactive and Mixed Initiative Decision Making*, pages 89–91, 1998.

[164] M. Elvang-Goransson, P. Krause, and J. Fox. Dialectic reasoning with incosistent information. In *Proceedings of the Ninth Conference*, pages 114–121, 1993.

[165] P.M. Dung. On the acceptability of arguments and its fundamental role in nonmonotonic reasoning, logic programming and n-person games. *Artificial Intelligence*, 77:321–357, 1995.

[166] T.J.M. Bench-Capon, H. Prakken, and G. Sartor. Argumentation in legal reasoning. In *Argumentation in Artificial Intelligence*, pages 363–382, 2000.

[167] C. Sierra, N.R. Jennings, P. Noriega, and S. Parsons. A framework for argumentation-based negotiation. In *International Workshop on Agent Theories, Architectures and Languages*, pages 177–192, 1997.

[168] S.D. Ramchurn, N.R. Jennings, and C. Sierra. Persuasive negotiation for autonomous agents: a rhetorical approach. In *IJCAI Workshop on Computational Models of Natural Argument, Mexico*, pages 9–17, 2003.

[169] F. Sadri, F. Toni, and P. Torroni. Logic agents, dialogues and negotiation an abductive approach. In *Proceedings of the AISB 2001 Symposium on Infromation Agents for E-Commerce*, 2001.

[170] D. Kahneman, P. Slovic, and Amos Tversky. *Judgment Under Uncertainty: Heuristics and Biases*. Cambridge University Press, Cambridge, UK, 1982.

[171] H. Simon. *Theories of Bounded Rationality*, pages 161–176. North Holland Publication Company, Amsterdam, 1972.

[172] H. Gimpel, N. Jennings, G. Kersten, A. Ockenfels, and C. Weinhardt. *Market Engineering: A Research Agenda*. Springer, Berlin, 2008.

[173] E.A. Durenard. *Professional Automated Trading: Theory and Practise*. John Wiley & Sons Inc., Hoboken, New Jersey, 2013.

[174] R. Lin, Y. Gal, S. Kraus, and Y. Mazliah. Traning with automated agents improves people's behavior in negotiation and coordination tasks. *Decision Support Systems*, 60:1–9, 2014.

[175] J. Broekens, C.M. Jonker, and J.-J. Ch. Meyer. Affective negotiation suport systems. *Journal of Ambient Intelligence and Smart Environments*, 2:121–144, 2010.

[176] K. Starke and A. Rangaswamy. Computer-mediated negotiations: review and research opportunities. *Encyclopedia of Microcomputers*, 26, 1999.

[177] A. Pommeranz, P. Wiggers, W.-P. Brinkman, and C.M. Jonker. Social acceptance of negotiation support systems: scenario-based exploration with focus groups and online survey. *Cognition, Technology and Work*, 14:299–317, 2011.

[178] A. Foroughi, W.C. Perkins, and M.T. Jelassi. An empirical study of an interactive, session-oriented computerized negotiation support system (nss). *Group Decision and Negotiation*, 4:485–512, 1995.

[179] C.M. Jonker, V. Robu, and J. Treur. An agent architecture for multi-attribute negotiation using incomplete preference information. *Autonomous Agents and Multi-Agent Systems*, 15:221–252, 2007.

[180] O.S. Oguz, A.Kucukyilmaz, T.M. Sezgin, and C. Basdogan. Collaborative haptic negotiation and role exchange in multimodal virtual environments. In *IEEE Haptics Symposium*, 2010.

[181] J.J. Horton and R.J. Zeckhauser. Algorithmic wage negotiations: Applications to paid crowdsourcing, 2010.

[182] A. Azaria, Y. Aumann, and S. Kraus. Automated agents for reward determination for human work in crowdsourcing applications. *Autonomous Agents and Multi-Agent Systems*, 98:934–955, 2014.

[183] G. Haim, Y. Gal, M. Gelfand, and S. Kraus. A cultural sensitive agent for human-computer negotiation. In *AAMAS '12 Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems, Valencia*, pages 451–458, 2012.

[184] S. Kraus and D. Lehmann. Designing and building a negotiating automated agent. *Computational Intelligence*, 11, 1995.

[185] R. Santos, G. Marreiros, C. Ramos, J. Neves, and J. Bulas-Cruz. Personality, emotion and mood in agent-based group decision making. *Intelligent Systems*, 26:1541–1672, 2011.

[186] R.R. McCrae and P.T. Costa. Validation of the five-factor model of personality across instruments and observers. *Journal of Personality and Social Psychology*, 52:81–90, 1987.

[187] L.J. Savage. *The Foundations of Statistics*. Dover Publications Inc., Mineola, New York, 1972.

[188] R. Selten. *What is Bounded Rationality*, pages 14–36. The MIT Press, Cambridge, MA, 2001.

[189] A. Rosenfeld and S. Kraus. Modeling agents based on aspiration adaptation theory. *Autonomous Agents and Multi-Agent Systems*, 24:221–254, 2012.

[190] Y. Gal and A. Pfeffer. Predicting people's bidding behavior in negotiation. In *AAMAS '06 Proceedings of the fifth international joint conference on Autonomous agents and multiagent systems , Japan*, 2006.

[191] R. Katz and S. Kraus. Efficient agents for cliff-edge environments with a large set of decision options. In *AAMAS '06 Proceedings of the fifth international joint conference on Autonomous agents and multiagent systems , Japan*, 2006.

[192] D. Traum, W. Swartout, S. Marsella, and J. Gratch. Fight, flight or negotiate: Believable strategies for conversing under crisis. In *International Workshop on Intelligent Virtual Agents 2005*, pages 52–64, 2005.

[193] C. Crothers. *Social Structure*. Routledge, London, 1996.

[194] M. Weber. The social causes of the decay of ancient civilization. *The Journal of General Education*, 5: 75–88, 1950.

[195] W.R. Scott. Reflections on a half-century of organizational sociology. *Annual Review Sociology*, 30:1–21, 2004.

[196] R. Lincoln and A.L. Kalleberg. *Culture, Control and Commitment: A Study of Work Organization and Work Attitudes in the United States and Japan*. Percheron Press, Clinton Corners, NY, 1990.

[197] M. Orru. *The economic organization of East Asian capitalism*, pages 297–310. 1997.

[198] D. Helbing. *Managing Complexity*, pages 285–299. 2012.

[199] J.M. Epstein. Why model? *Journal of Artificial Societies and Social Simulation*, 11, 2008.

[200] C.M. Jonker and J. Treur. A formal approach to building compositional agent-based simulations. In B. Edmonds and R. Meyer, editors, *Simulating Social Complexity: A Handbook*. 2013.

[201] R. Mercuur, V. Dignum, and C.M. Jonker. The value of values and norms in social simulation. *Journal of Artificial Societies and Social Simulation*, 22, 2019.

[202] R.K. Sawyer. Interpreting and understanding simulations: The philosophy of social simulation. In B. Edmonds and R. Meyer, editors, *Simulating Social Complexity: A Handbook*. 2013.

[203] K.G. Troitzsch. Historical introduction. In B. Edmonds and R. Meyer, editors, *Simulating Social Complexity: A Handbook*. 2013.

[204] O. Barreteau, P. Bots, K. Daniell, M. Etienne, P. Perez, C. Barnaud, D. Bazile, N. Becu, J.-C. Castella, W. Dare, and G. Trebuil. Participatory approaches. In B. Edmonds and R. Meyer, editors, *Simulating Social Complexity: A Handbook*. 2013.

[205] C.L.K. Kawada, G. Oettingen, P.M. Gollwitzer, and J.A. Bargh. The projection of implicit and explicit goals. *Journal of Personality and Social Psychology*, 86:545–559, 2004.

[206] A. Fishback and M.J. Ferguson. The goal construct in social psychology. In A.W. Kruglanski and E.T. Higgins, editors, *Social psychology: Handbook of basic principles*, pages 490–515. 2007.

[207] E.L. Deci and R.M. Ryan. *Intrinsic Motivation and Self-Determination in Human Behavior*. Springer, Boston, MA., 1985.

[208] R. Conte, B. Edmonds, S. Moss, and R.K. Sawyer. Sociology and social theory in agent based social simulation: A symposium. *Computational and Mathetmatical Organization Theory*, 7:183–205, 2001.

[209] I. van de Poel and L. Royakkers. *Ethics, Technology and Engineering: An Introduction*. Wiley-Blackwell, Hoboken, New Jersey, 2011.

[210] L.D. Miles. *Techniques of Value Analysis and Engineering*. Eleanor Miles Walker, 1989.

[211] S.H. Schwartz, J. Cieciuch, M. Vecchione, E. Davidov, R. Fisher, C. Barlerlein, A. Ramos, M. Verkasalo, J.-E. Lonnqvist, K. Demirutku, O. Dirilen-Gumus, and M. Kontey. Refining the theory of basic individual values. *Journal of Personality and Social Psychology*, 103:663–688, 2012.

[212] G.P. Latham. *Work Motivation: History, Theory, Research and Practice*. Sage, Los Angeles, 2012.

[213] E.L. Deci and R.M. Ryan. The general causality orientations scale: Self-determination in personality:. *Journal of Research in Personality*, 19:109–134, 1985.

[214] A. Sharpanskykh and R. Haest. An agent-based model to study compliance with safety regulations at an airline ground service organization. *Applied Intelligence*, 45:881–903, 2016.

[215] J.S. Eccles and A. Wigfield. Motivational beliefs, values and goals. *Annual Review of Psychology*, 53: 109–132, 2002.

[216] B. Weiner. On sin versus sickness: A theory of perceived responsibility and social motivation. *American Psychologist*, 48:957–965, 1993.

[217] C.C. Pinder. *Work Motivation in Organizational Behavior*. Prentice Hall, Upper Saddle River, New Jersey, 1998.

[218] A. Grow, A. Flache, and R. Wittek. An agent-based model of status construction in task focused groups. *Journal of Artificial Societies and Social Simulation*, 18:4, 2015.

[219] M. Wooldridge and N.R. Jennings. The cooperative problem solving process. *Journal of Logic and Computation*, 9:563–592, 1999.

[220] J.A. Rojas-Villafane. *An Agent-based Model of Team Coordination and Performance*. PhD thesis, Florida International University, 2010.

[221] R.M. Crowder, M.A. Robinson, H.P.N. Hughes, and Y.-W. Sim. The development of an agent-based modeling framework for simulating engineering team work. *IEEE Transactions on Systems, Man and Cybernetics - Part A: Systems and Humans*, 42, 2012.

[222] M.E. Gaston and M. DesJardins. The effect of network structure on dynamic team formation in multi-agent systems. *Computational Intelligence*, 24, 2008.

[223] N.V. Findler and R.M. Malyankar. An empirical approach to a theory of coordination. part i: Design principles and first results. *Computational and Mathematical Organization Theory*, 6:119–144, 2002.

[224] B. Dunin-Keplicz and R. Verbrugge. *Teamwork in Multi-Agent Systems*. Jon Wiley and Sons, Hoboken, New Jersey, 2010.

[225] F.L. Ulschak, L. Nathanson, and P.G. Gillan. *Small group problem solving: an aid to organizaitonal effectiveness*. Addison-Wesley, 1981.

[226] D. Hales. Group reputation supports beneficent norms. *Journal of Artificial Societies and Social Simulation*, 5:1–4, 2002.

[227] V. Palmer. Simulation of the categorization-elaboration model of diversity and work-group performance. *Journal of Artificial Societies and Social Simulation*, 9:1–3, 2006.

[228] A. Nowak, M.E. Miller, and R.R. Vallacher. *Social Influence and Group Dynamics*. Wiley & Sons, 2003.

[229] R.B. Cialdini and M.R. Trost. *Social norms, conformity and compliance*, pages 151–192. New York, NY, 1998.

[230] R.B. Cialdini and M.R. Trost. *Social norms, conformity and compliance*, pages 151–192. New York, NY, 1998.

[231] A.M. Colman. *A Dictionary of Psychology*. Oxford University Press, 2015.

[232] H.C. Kelman. Compliance, identification and internalization: Three processes of attitude change. *Journal of Conflict Resolution*, 2:51–60, 1958.

[233] P. Bachrach and M.S. Baratz. Decisions and nondecisions: an analytical framework. *American Political Science Review*, 57:632–642, 1963.

[234] C. Sibertin-Blanc, P. Roggero, F. Adreit, B. Baldet, P. Chapron, J. El-Gemayel, M. Mailliard, and S. Sandri. Soclab: A framework for the modeling, simulation and analysis of power in social organizations. *Journal of Artificial Societies and Social Simulation*, 16:8–34, 2013.

[235] B.H. Raven. A power/interaction model of interpersonal influence: French and raven thirty years later. *Journal of Social Behavior* & *Personality*, 7:217–244, 1992.

[236] D. Passenier, C. Mols, J. Bim, and A. Sharpanskykh. Modeling safety culture as a socially emergent phenomenon: a case study in aircraft maintenance. *Computational and Mathematical Organization Theory*, 22: 487–520, 2016.

[237] R.L. Peabody. *Organizational Authority: Superior-Subordinate Relationships in Three Public Service Organizations*. Atherton Press, 1964.

[238] F. Giardini, R. Conte, and M. Paolucci. Reputation. In B. Edmonds and R. Meyer, editors, *Simulating Social Complexity: A Handbook*. 2013.

[239] C.D. Frith and U. Frith. The neural basis of mentalizing. *Neuron*, 50:531–534, 2006.

[240] M. Fishbein and I. Ajzen. *Predicting and Changing Behavior*. Taylor & Francis, Oxfordshire, United Kingdom, 2011.

[241] M. Neumann. Social constraint. In B. Edmonds and R. Meyer, editors, *Simulating Social Complexity: A Handbook*. 2013.

[242] E. Ostrom and S.E.S. Crawford. *Classifying rules*. Princeton University Press, Princeton, New Jersey, 2005.

[243] R. Axelrod. An evolutionary approach to norms. *The American Political Science Review*, 80:1095–1111, 1986.

[244] A. Garcia-Camino, J. A. Rodriguez-Agiular, and W. Vasconcelos. Norm-oriented programming of electronic institutions: a rule-based approach. In H. Nakashima, M. Wellman, G. Weiss, and P. Stone, editors, *Proceedings of the 5th international joint conference on autonomous agents and multi-agent system*, New York, NY, 2006. ACM Press.

[245] F. Dignum, D. Kinny, and L. Sonenberg. From desires, obligations and norms to goals. *Cognitive Science Quarterly*, 2, 2002.

[246] G. Boella and L.W.N. van der Torre. Norm governed multiagent systems: The delegation of control to autonomous agents. In *proceedings of the IEEE/WIC international conference on intelligent agent technology*, pages 329–335, 2003.

[247] M.R. Endsley. Toward a theory of situation awareness in dynamic systems. *Human Factors Journal*, 37: 32–64, 1995.

[248] H.A.P. Blom and A. Sharpanskykh. Modelling situation awareness relations in a multiagent system. *Applied Intelligence*, 43:412–423, 2015.

[249] M.R. Endsley and M.M. Robertson. Situation awareness in aircraft maintenance teams. *International Journal of Industrial Ergonomics*, 26:301–325, 2000.

[250] J. Kolodner. *Case-based reasoning*. Morgan Kaufmman Publishers, San Mateo, California, 1993.

[251] I. Watson. *Case-Based Reasoning is a Methodology not a Technology*. Springer-Verlag, London, UK, 1999.

[252] J.L. Kolodner. An introduction to case-based reasoning. *Artificial Intelligence Review*, 6:3–34, 1992.

[253] V. Dignum and F. Dignum. Contextualized planning using social practices. In *International Workshop on Coordination, Organizations, Institutions, and Norms in Agent Systems*, pages 36–52, 2015.

[254] R. Mercuur, V. Dignum, and C.M. Jonker. Modelling agents endowed with social practices. A Preprint `https://www.researchgate.net/publication/329234814_Modelling_Agents_Endowed_with_Social_Practices_Static_Aspects`, 2018.

[255] P. Bourdieu. *Outline of a theory of practice*, volume 16. Cambridge University Press, 1977.

[256] T.R. Schatzki. *Site of the Social?: A Philosophical Account of the Constitution of Social Life and Change*. Pennsylvania State University Press, 2002.

[257] A. Reckwitz. Toward a theory of social practices - a development in culturalist theorizing. *European Journal of Social Theory*, 5:243–263, 2002.

[258] A.y Giddens. *The Constitution of Society: Outline of the Theory of Structuration*. University of California Press, 1984.

[259] E. Shove, M. Pantzar, and M. Watson. *The Dynamics of Social Practice Theory*. SAGE Publications, London, UK, 2012.

[260] K. Narasimhan, T. Roberts, M. Xenitidou, and N. Gilbert. Using abm to clarify and refine social practice theory. In W. Jager, R. Verbrugge, A. Flache, G. de Roo, L. Hoogduin, and C. Hemelrijk, editors, *Advances in Social Simulation 2015*, Advances in Intelligent Systems and Computing. Springer, 2017.

[261] R.Mercuur. Interventions on contextualized decision making: an agent-based simulation study. Master's thesis, Utrecht Univeristy, 2015.

[262] T. Kurz, B. Gardner, B. Verplanken, and C. Abraham. Habitual behaviors or patterns of practice? explaining and changing repetitive climate-relevant actions. *Wiley Interdisciplinary Reviews: Climate Change*, 6:113–128, 2014.

[263] Effort. In cambridge dictionary. Retrieved March 5th, 2020 from: `https://dictionary.cambridge.org/dictionary/english/effort`.

[264] R.M Ryan and E.L. Deci. Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary Educational Psychology*, 25:54–67, 2002.

[265] M. Csikszentmihalyi. *Beyond boredom and anxiety*. Jossey-Bass, 2000.

[266] Group. In cambridge dictionary. Retrieved March 13th, 2020 from `https://dictionary.cambridge.org/dictionary/english/group`.

[267] Impression. In oxford dictionary. Retrieved March 13th, 2020 from `https://www.lexico.com/definition/impression`.

[268] L. Legault. *The Need for Competence*, pages 1–3. Springer International Publishing, 2017.

[269] A.H. Maslow. Higher and lower needs. *The Journal of Psychology: Interdisciplinary and Applied*, 25:433–436, 1948.

[270] Performance. In cambridge dictionary. Retrieved March 13th, 2020 from `https://dictionary.cambridge.org/dictionary/english/performance`.

[271] D. Levi. *Social Influence and Power*. SAGE Publications, 2007.

[272] L. Mui, M. Mohtashemi, and A. Halberstadt. A computational model of trust and reputation. In *Proceedings of the 35th Annual Hawaii International Conference on System Sciences*, pages 2431–2439, 2002.

[273] R. Razzouk and T.E. Johnson. *Shared Cognition*. 2012.

[274] M.R. Endsley, R.J. Hansman, and T.C. Farley. Shared situation awareness in the flight deck-atc system. *IEEE Aerospace and Electronic Systems Magazine*, 14:25–30, 1999.

[275] Skill. In cambridge dictionary. Retrieved March 13th, 2020 from `https://dictionary.cambridge.org/dictionary/english/skill`.

[276] Task. In cambridge dictionary. Retrieved March 13th, 2020 from `https://dictionary.cambridge.org/dictionary/english/task`.

[277] S.A.S. Baron. *Dynamic Task Allocation and Coordination in Cooperative Multi-agent Environments*. PhD thesis, University of Girona, 2010.

[278] Thoroughness. In cambridge dictionary. Retrieved March 13th, 2020 from `https://dictionary.cambridge.org/dictionary/english/thoroughness`.

[279] Efficiency. In online dictionary. Retrieved March 13th, 2020 from `https://www.dictionary.com/browse/efficiently`.

[280] A.C. Bluedorn and R.B. Denhardt. Time and organizations. *Journal of Management*, 14, 1988.

[281] D. Rousseau, S. Sitkin, R. Burt, and C. Camerer. Not so different after all: A cross-discipline view of trust. *Academy of Management Review*, 23:393–404, 1998.

[282] J. Surowiecki. *The Wisdom of crowds: why the many are smarter than the few and how collective wisdom shapes business, economies, societies and nations*. Doubleday; Anchor, 2004.

[283] T. Mussweiler. Comparison processes in social judgment: Mechanisms and consequences. *Psychological Review*, 110:472–489, 2003.

[284] S. Morse and K.J. Gergen. Social comparison, self-consistency, and the concept of self. *Journal of Personality and Social Psychology*, 16:148–156, 1970.

[285] M.B. Brewer and J.G. Weber. Self-evaluation effects of interpersonal versus intergroup social comparison. *Journal of Personality and Social Psychology*, 66:268–275, 1994.

[286] A. Vargha and H.D. Delaney. A critique and improvement of the cl common language effect size statistics of mcgraw and wong. *Journal of Educational and Behavioral Statistics*, 25(2):101–132, 2000.

[287] A. Sharpanskykh. Week 3: Agent-based simulation. analysis of simulations results. model validation. slides of agent-based modelling and simulation course. tu delft. unpublished document. 2019.

[288] M. Ben-Akiva and M. Bierlaire. *Discrete choice methods and their applications to short term travel decision*, pages 5–33. Springer, 1999.