Simulation-based Optimization and Decision Making with Imperfect Information

FARZAD KAMRANI

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Tryck: Universitetsservice US AB
To my beloved Soheila,
and my parents Soroush and Vali.
Abstract

The purpose of this work is to provide simulation-based support for making optimal (or near-optimal) decisions in situations where decision makers are faced with imperfect information. We develop several novel techniques and algorithms for simulation-based optimization and decision support and apply them to two categories of problems: (i) Unmanned Aerial Vehicle (UAV) path planning in search operations, and; (ii) optimization of business process models. Common features of these two problems for which analytical approaches are not available, are the presence of imperfect information and their inherent complexity.

In the UAV path planning problem, the objective is to define the path of a UAV searching for a target on a known road network. It is assumed that the target is moving toward a goal and we have some uncertain information about the start point of the target, its velocity, and the final goal of the target. The target does not take evasive action to avoid being detected. The UAV is equipped with a sensor, which may detect the target once it is in the sensor’s scope. Nevertheless, the detection process is uncertain and the sensor is subject to both false-positive and false-negative errors. We propose three different solutions, two of which are simulation-based. The most promising solution is an on-line simulation-based method that estimates the location of the target by using a Sequential Monte Carlo (SMC) method. During the entire mission, different UAV paths are simulated and the one is chosen that most reduces the uncertainty about the location of the target.

In the optimization of the business process models, several different but related problems are addressed: (i) we define a measure of performance for a business process model based on the value added by agents (employees) to the process; (ii) we use this model for optimization of the business process models. Different types of processes are distinguished and methods for finding the optimal or near-optimal solutions are provided; (iii) we propose a model for estimating the performance of collaborative agents. This model is used to solve a class of Assignment Problems (AP), where tasks are assigned to collaborative agents; (iv) we propose a model for team activity and the performance of a team of agents. We introduce different collaboration strategies between agents and a negotiation algorithm for resolving conflicts between agents. We compare the effect of different strategies on the output of the team.

Most of the studied cases are complex problems for which no analytical solution is available. Simulation methods are successfully applied to these problems. They are shown to be more general than analytical models for handling uncertainty since they usually have fewer assumptions and impose no restrictions on the probability distributions involved. Our investigation confirms that simulation is a powerful tool for providing decision-making support. Moreover, our proposed algorithms and methods in the accompanying articles contribute to providing support for making optimal and in some cases near-optimal decisions: (i) our tests of the UAV simulation-based search methods on a simulator show that the on-line simulation method has generally a high performance and detects the target in a reasonable time. The performance of this method was compared with the detection time when the UAV had the exact information about the initial location of the target, its velocity, and its path (minimum detection time). This comparison indicated that the on-line simulation method in many cases achieved a near-optimal performance in the studied scenario; (ii) our business process optimization framework combines simulation with the Hungarian method and finds the optimal solution for all cases where the assignment of
tasks does not change the workflow of the process. For the most general cases, where
the assignment of tasks may change the workflow, we propose an algorithm that finds
near-optimal solutions. In this algorithm, simulation, which deals with the uncertainty
in the process, is combined with the Hungarian method and hill-climbing heuristics. In
the study of assigning tasks to collaborative agents we suggest a Genetic Algorithm (GA)
that finds near-optimal solutions with a high degree of accuracy, stability, scalability and
robustness. While investigating the effect of different agent strategies on the output of a
team, we find that the output of a team is near-optimal, when agents choose a collabora-
tion strategy that follows the principle of least effort (Zipf’s law) and use our suggested
algorithm for negotiation and resolving conflicts.
Sammanfattning

Syftet med detta arbete är att tillhandahålla simuleringbaserat stöd för att fatta optimala (eller nära optimala) beslut i situationer där beslutsfattare konfronteras med ofullständig information. Vi utvecklar flera nya tekniker och algoritmer för simuleringsbaserad optimering samt tillämpar dem på två kategorier av problem: (i) färdvägsplanering för obemannade luftfarkoster (UAV) i ett sökuppdrag, och; (ii) optimering av affärsprocesser. Gemensamt för dessa båda problem, för vilka analytiska metoder saknas, är att informationen är ofullständig och att de har en inneboende komplexitet.


I fallet optimering av affärsprocesser diskuteras flera relaterade men olika problem: (i) vi definierar ett mått på prestanda för en affärsprocess baserad på mervärdet som skapas av agenter (personal) i processen; (ii) vi använder denna modell för optimering av affärsprocesser. Olika typer av processer särskiljs och metoder för att hitta optimala eller nära optimala lösningar föreslås; (iii) vi föreslår en modell för att uppskatta resultatet av samverkande agenter. Denna modell används för att lösa en kategori av tilldelningsproblem (AP), där uppgifter tilldelas till samverkande agenter; (iv) vi föreslår en modell för teamaktivitet och prestanda hos ett team av agenter. Vi presenterar olika samarbetsstrategier mellan agenter och en förhandlingsalgoritm för att lösa konflikter mellan dessa. Vi jämför effekten av olika strategier för teamets prestanda.

De flesta av de studerade fallen är komplexa problem, för vilka det inte finns några kända analytiska lösningar. Simuleringsmetoder tillämpas med framgång på dessa problem. Dessa visar sig mer generella än vad analytiska modeller är för hantering av osäkerhet eftersom de oftast har färre antaganden och inte medför några restriktioner för de inkludade sannolikhetsfördelningsarna. Vår undersökning bekräftar att simulering är en kraftfull metod för beslutsstöd. Dessutom ger våra föreslagna algoritmer och metoder i medföljande artiklar stöd för att hitta optimala och i vissa fall nära optimala lösningar: (i) våra simuleringsexperiment av färdvägsplanering för UAV visar att online-simuleringsmetoden generellt har en hög prestanda och upptäcker målet inom rimlig tid. Prestandan hos denna metod jämfördes med upptäcktstiden när UAV:n hade exakt information om målets startposition, dess hastighet och dess bana (minimal upptäcktstid). Jämförelsen visade att online-simuleringsmetoden i många fall uppnår en nära optimal prestanda i det studerade scenariot. (ii) vårt optimeringsramverk för affärsprocesser kombinerar simulering med Hungarian-metoden och hittar den optimala lösningen för de fall där tilldelning av uppgifter inte ändrar arbetsflödet i processen. För de mest generella fallen där tilldelningen kan ändra arbetsflödet, föreslår vi en algoritm som hittar nära optimala lösningar. Simulering, som användas för att hantera osäkerheten i processen, kombineras i denna algoritm med Hungarian-metoden och en Hill-climbing heuristic metod. I studien om tilldelning
av uppgifter till samverkande agenter föreslår vi en genetisk algoritm som finner nära optimala lösningar med en hög grad av noggrannhet, stabilitet, skalbarhet och robusthet. Undersökning av effekten av olika agentstrategier visar att prestandan hos ett team är nära optimal när agenterna väljer en samarbetsstrategi som följer priset om minsta ansträngning (Zipfs lag) samt använder vår föreslagna algoritm för förhandling och lösning av konflikter.
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![](https://example.com/image)
Part I

Thesis Overview
Chapter 1

Introduction

The decision making process depends heavily on the underlying information and its quality. From the decision-makers’ point of view, the ideal scenario is when all available information is precise, consistent, certain and correct. This situation is hardly attained in real life. Consequently, decision makers are forced to base their decisions on imprecise and uncertain information. In this chapter, we give an introduction to these concepts and their impact on the decision making process.

1.1 Imperfect Information

The problem of whether uncertainty is an inherent part of nature is still an open question. Regardless of the answer to this question, it must be recognized that our picture of the world is never complete. The information available to us is always somehow imperfect [1]. Information may be imperfect due to several reasons. For example, it may be about future events, it may describe the unknown state of (current or past) affairs, or it may be based on imprecise measurements.

We adopt the categorization of information as discussed by Smets [1] and distinguish between perfect and imperfect information. Information is perfect when it is precise, certain and consistent. Thus, if one (or more) of these attributes is not present, the information is imperfect. Perfect information does not necessarily mean that it is true. Information can be precise, certain and consistent (with other pieces of information) but wrong. If you state “I am sure John has three children”, this would be a precise and certain statement. However, it would be false if John in fact has only two children. To believe $p$ does not mean that $p$ is indeed true. You can be wrong [2].

Information can be imperfect due to imprecision, inconsistency or uncertainty. Imprecision and inconsistency are mainly properties of the information per se. One way to define information is to describe it as a means to determine which world among a set of possible worlds is the actual world [2]. Given inconsistent information, no world is compatible with the available information, whereas imprecision
means more than one world can be found in accordance with the information. Uncertainty is a property related to the lack of information about the world. The definition of uncertainty involves the concept of an agent that uses the information. Information is uncertain if it does not provide the agent with the ability to decide about the exact state of real world [2].

Uncertainty and imprecision are distinct, but they often coexist and are related. As Smets states: “Often the more imprecise you are, the most certain you are, and the more precise, the less certain. There seems to be some Information Maximal-ity Principle that requires that the 'product' of precision and certainty cannot be beyond a certain critical level. Any increase in one is balanced by a decrease in the other [1].”

1.1.1 Imprecision

Imprecise information (a statement about the world) cannot distinguish a unique world in the set of all possible worlds that satisfy the statement. Imprecise information may be approximate (‘John is about 1.80 cm’) or fuzzy (‘John is tall’). Imprecise information may be without error or combined with error. Inaccurate information has a small error, for example (‘John is 1.81 cm’ when his actual height is 1.82 cm). Information will be erroneous or incorrect when it is wrong (‘John is 1.65 cm’ when his height is 1.82 cm). Information is biased if it is based on data that are subject to systematic errors. For example, if all heights were given as true height plus 3 cm. Meaningless information is an extreme aspect of erroneous when the error is so extreme that the user can discover it instantaneously: ‘John is 18 cm’. [1]

1.1.2 Inconsistency

Like imprecision, inconsistency is also essentially a property of the information itself. It can arise when several pieces of information are combined. The conflict in the data leads to incoherence in the conclusions: ‘John is 182 cm and Jane is 165 cm height’, ‘Jane is taller than John’. No world in the set of all possible worlds satisfies both these statements. [1]

1.1.3 Uncertainty

Whereas, imprecision is a characteristic of the information itself, uncertainty is a property that depends on both the data and the agent. Uncertain information is related to the state of confidence of an agent about the world. When you state ‘I believe John is taller than Jane’, the statement ‘John is taller than Jane’ is either true or false. However, your knowledge about the world does not allow you to decide if the statement is true or false. Uncertainty is essentially induced by the partial absence of information [1, 2].
Despite the philosophical debates about whether uncertainty is an objective or a subjective property, most literature classifies uncertainty into two categories: **objective uncertainty** and **subjective uncertainty** [1–4].

**Objective uncertainty:** Objective uncertainty also called *aleatory* or *irreducible* uncertainty is due to inherent randomness of the process. Objective uncertainty cannot be reduced or eliminated, e.g. the outcome of a die toss or the actual length of a manufactured product with a nominal value. Obviously, after observing the outcome of the die, the uncertainty is reduced (practically to zero, if you trust your eyes). The situation is the same if the part is manufactured and you measure the length of the product. However, your uncertainty cannot be reduced before these events happen.

One may argue that it is possible to reduce the uncertainty by modifying the production process or quality control; nevertheless, for the given configuration, the uncertainty due to manufacturing is considered irreducible [3].

**Subjective uncertainty:** Subjective uncertainty also called *epistemic* or *reducible* uncertainty is uncertainty that is related to the lack or incompleteness of information. As new data (sensor observation), information (e.g. improved numerical approximation), or knowledge (expert opinion) becomes available, the uncertainty can be reduced. If sufficient knowledge is added, then the epistemic uncertainty can, in principle, be eliminated [1, 3].

Sometimes, it is difficult to determine the distinction between objective and subjective uncertainty. For instance, we may model the weight of infants at birth in an ethnic group by a probability distribution (objective uncertainty). However, if we derive this distribution from a very small sample of the population, then the obtained distribution probably differs from the true underlying distribution. Consequently, the uncertainty in the weight of infants is a combination of objective and subjective uncertainty. By increasing the sample size (adding information), the probability distribution would be a more accurate estimation of the underlying distribution. The subjective uncertainty reduces, whereas the objective uncertainty remains unchanged. By using a large number of samples, the subjective uncertainty is almost removed [3].

### 1.2 Decision Making with Imperfect Information

Decision making may be a challenging task due to different reasons, among them imperfection of information, complexity of the problem at hand, involvement of multiple objectives, or a combination of some of the above. Decision makers are rarely able to tackle these difficulties efficiently, something that has led to the emergence of *Decision Support Systems (DSS)*.

Human difficulty to understand and manage uncertainty has been discussed in the literature over the years. Tversky and Kahneman [5] found that people rely on a
number of heuristic principles to reduce the complex task of assessing probabilities. In general, these heuristics are quite useful, but sometimes they lead to bias in judgments, and systematic errors. Moreover, they suggested that these types of fallacy are not restricted to laymen and even experienced researchers are prone to the same biases when facing uncertainty.

Complex problems require that information is compiled. While humans are superior in some aspects of information processing, their capacity is very limited compared with computer systems to process large amount of information. If the amount of information that should be processed in order to derive decisions overwhelms human cognitive capability (specially when information is imprecise) the use of DSS is inevitable.

1.3 Types of Decision Makers

Decision makers can be classified into two main categories Individual decision makers and Multiple decision makers [6]. We consider multiple decision makers to be out of the scope of this thesis. Individual decision making is either human-based (a single person) or machine-based (a computer system).

Alter [7] uses a taxonomy based on degree of action implication of system output i.e., the degree to which the system’s output could directly determine the decision, to categorize DSSs. That is a decision support system is categorized according to a generic operation regardless of the type of the problem and the domain. These generic operations are ranged from extremely data oriented to extremely model oriented:

1. retrieving a single item of information
2. providing a mechanism for ad hoc data analysis
3. providing prespecified aggregation of data (reports)
4. estimating the consequences of decisions proposed by humans
5. proposing decisions, and
6. making decisions [7].

Only systems characterized in the last two cases can provide support at such levels that human intervention may be removed and we achieve machine-based decision making.

1.3.1 Human-based Decision Making

A solely human-based decision process is inefficient and prone to errors; therefore, DSS has increasingly become part of the decision making in a wide range of areas. With human-based decision making, we mean a process in which the final decision
maker is human, although he/she may employ the assistance of computer systems in different parts of the process and in various degrees.

The opinion about whether it is possible for computer systems to become as intelligent as humans is sharply divided (e.g. see Searle’s Chinese room argument [8] or Penrose’s books [9, 10] arguing against AI and McCarthy’s refutation of their idea [11–13]). Nevertheless, it is commonly accepted that existing computers in many areas are far behind human capabilities. Human beings are particularly strong in communication, symbolic reasoning, conceptualization, learning, and intuition. Human pattern recognition is not limited to visual perception and applies also to abstract concepts and intuitive notions. These characteristics equip humans with the capability of situational awareness even in a fairly chaotic environment [14]. However, as Pohl [15] describes, these strengths are vulnerable to emotional influences which can easily bias humans’ decisions. Consequently, he proposes a partnership between humans and computers (in preference to automation) to overcome the human weaknesses in decision making.

1.3.2 Machine-based Decision Making

Decision making is a process focused on finding the best course of action. In machine-based decision making, this process is completed without human intervention. If the decision is also executed by a machine, we have achieved a fully autonomous system. Removing the human from the process is a radical measure that implies certain prerequisites on the problem to be solved. Automation technology is still in its infancy and can generally address only well-defined (well-structured) problems.

According to one of the earliest papers in the field of Artificial Intelligence (AI), a well-defined problem is one for which it is possible to test mechanically whether or not a proposed answer is a valid solution [16]. All other problems are considered to be ill-defined (ill-structured).

During the past decades, this original definition has been discussed and re-examined by a number of researchers, each approaching the topic with a different purpose and focus [17, 18]. Researchers in the field of cognitive science usually draw a more sharp distinction between the two categories, e.g. see [19, 20]. They suggest that there are some nontrivial differences between ill-defined and well-defined problem spaces. In the field of AI, which generally has a more optimistic view about the ability of computers to address even ill-defined problems [13, 21], this distinction is not always accepted. Simon [22] considers the definedness of a problem as a continuous spectrum ranging from ill-defined to well-defined. He suggests that there is no reason to suppose that new and unknown concepts or techniques are needed to enable AI to solve ill-defined problems. Lynch et al. [17, 18] provide an overview of the discussions about the topic and add some details to the definition of ill-defined problems related to research in AI and Education. In their opinion, domains like law, ethics, history, public policy, and architecture are inherently ill-defined, which
implies that most of the problems in these domains are ill-defined. Hence, these
domains are differentiated from domains such as Newtonian mechanics.
Here, we find the definition provided by [23, 24] sufficient for our purpose: a
well-defined problem is one that has a clear specification of the start-state and goal-
state and a clear set of permissible operations, i.e. legal moves from each state in
the problem space. In contrast, an ill-defined problem includes a vaguely specified
start state, goal state, or set of operations.
For example, winning a chess match against a grandmaster is a well-defined (but
complex) problem. To be more correct, one should say a chess match is a sequence
of well-defined problems each corresponding to a single move. In each move, the
start state, the goal-state (best-move) and the set of legal moves are well-defined.
However, due to the computational complexity, the best-move is usually substituted
by a move that maximizes some approximate evaluation function. [22].
On the contrary, the problem of “how I can improve the quality of this thesis?” is
an ill-defined problem, since there is no clear start and end state. Furthermore, the
concept of quality of a thesis is under-specified. Even if one rigorously defines the
quality of a thesis, the steps toward improving such a quality will still be unknown.
A necessary requirement for a decision process to be machine-based is that the
problem at hand is either well-defined or it can be decomposed to parts, most of
which are well-defined. However, well-definedness is not a sufficient condition. For
example, the Chinese game of Go (“Weiqi” in Chinese) has simple rules and can be
considered as a well-defined problem; however, there is still no computer program
that performs well compared to a moderately strong player [13].

1.4 Simulation Based Decision Making
Simulation-based DSS refers to a category of DSS in which simulation is used
as one of the (main) components of the system. The decision problem consists
of a set of available decision alternatives and an objective function representing
the preferences of the decision maker. The alternatives are compared using an
appropriate simulation model, which may incorporate uncertain data. The decision
alternatives constitute the input parameters of the simulation model. Then, based
on the simulation output, the optimal decision is distinguished or alternatives are
ranked.
Advantages associated with the use of simulation in DSS and optimization prob-
lems are widely acknowledged in the literature. Here, we do not intend to provide
an exhaustive list of these advantages. Rather, we highlight those aspects that we
have experienced as most important in our work.
- Simulation models can be used for extremely complex problems, where an-
  alytical approaches are not available. They explicitly account for physical
  processes and give a more complete description of reality. They permit to
  incorporate various interactions and correlations and capture more of the real
  world complexities.
Simulation models have the ability to incorporate random events and imperfect information. They are more general than analytical models for uncertainty and usually have fewer assumptions and impose no restrictions on the probability distributions involved.

Simulation models can conveniently be combined with other analytical, or numerical methods and provide a single integrated model.

Simulation approaches can readily be combined with different optimization methods and techniques.

In the following section we discuss two types of simulation-based decision support systems used in: (1) Unmanned Aerial Vehicle (UAV) path planning in search operations, (2) optimization of business process assignments to agents. Although these two types of problems belong to completely different domains, they have some common characteristics both in the problem domain and in the provided solution:

- Imperfect information is an inherent part of the problem.
- Simulation is used as the main method for optimization.
- A decision is made based on optimization of an objective function.

However, the main difference in the two systems is that in the former case the decision is implemented by the UAV system, and the decision making can be considered as machine-based, while in the latter case the most beneficial decision is proposed to decision makers for possible implementation.
Chapter 2
Problem Description and Solution
Overview

In this section, we discuss two simulation-based decision support systems addressing two different types of problems: (1) UAV path planning in search operations; (2) business process assignments to agents. Both of these problems are complex problems with imperfect information, for which no analytical solutions are available. The existence of imperfect information introduces new challenges to the decision process. The problem is twofold: (1) how to model imperfect information; (2) how to overcome the computation complexity resulting from the presence of imperfect information, which frequently leads to very large-scale state space.

Here, we present a general description of the problems and give an overview of the solutions and the main employed methodologies. Several different flavors of the problems and the corresponding solutions are fully explained by papers in the second part of this thesis.

2.1 UAV Path Planning

In papers 1, 2 and 3 in part II of this thesis, we address UAV path planning. More specifically, we address the problem of defining the path of a single UAV in a search operation. A UAV has the task to localize a single target moving on a known road network by scanning an area of interest selectively. It is assumed that the target is moving toward a goal; however, it does not take evasive action to avoid being detected. Prior to the operation, we have some uncertain information about the start point, the final destination, and the velocity of the target. The UAV is equipped with a sensor, which may detect the target once it is in the sensor’s scope. Nevertheless, the detection process is uncertain and the sensor is subject to both false-positive and false-negative errors.

We provide three different solutions to the problem: (i) a search method that traverses all road segments in a topological sort in a manner which guarantees that
the target will be found; (ii) an off-line simulation-based search method that before the start of the mission simulates the future location of the target and compares the expected time of the detection of the target for different UAV paths; (iii) an online simulation-based search method, that uses simulation during the entire search mission and incorporates the sensor observation to update the target estimation. The on-line simulation is synchronized with the control of the UAV at certain time-points. During each simulation period, the path that most reduces the uncertainty about the location of the target is preferred.

These methods are tested on a special purpose simulation tool. The methods are compared on similar test scenarios. The on-line simulation-based search method shows to be more efficient compared with the off-line method, which in turn is more efficient than the exhaustive search. In the rest of this section, we focus on the on-line simulation-based method, since it is the most efficient and interesting one.

2.1.1 Overview of the On-line Simulation Method

The on-line simulation method can be described as follows: A sequence of time-points \(\{t_0, t_1, \ldots\}\), where \(t_0\) is the start time of the mission, is defined. At \(t_0\), a default (random) path for the UAV is chosen. At each subsequent time-point \(t_k \in \{t_1, t_2, \ldots\}\), a set of simulations with alternative UAV paths are started. In each simulation, the state of the target at time \(t \geq t_k+1\) and the effect of choosing the specific UAV path is estimated. These simulations are completed during the time period \([t_k, t_{k+1}]\) and the UAV path that performs best is distinguished. At time \(t_{k+1}\) this path is chosen as the future path of the UAV and the procedure is repeated by starting a new set of simulations. These simulations that are initiated and executed periodically after reaching time-points run faster than real-time and are executed concurrently.

Sensor outputs (or lack of outputs) continuously modify the estimation of the location of the target, but this updated information is used first at the next time-point. That is, sensor information during time period \([t_k, t_{k+1}]\) affects simulations performed in period \([t_{k+1}, t_{k+2}]\), which determine the path of the UAV after time \(t_{k+2}\). The sensor data, before detection of the target, consists mostly of “negative” information i.e. lack of sensor measurement where it was (with some probability) expected [25]. Starting from the uncertain information about the initial state of the target, sensor data continuously and in real-time update our estimation of the target’s location.

A general framework for estimating an unknown probability distribution using incoming sensor data is recursive Bayesian estimation, which is briefly described in the following subsection.
2.1.2 Recursive Bayesian Estimation

Roughly speaking, recursive Bayesian estimation is a method, which repeatedly predicts the new state of a system according to a transition model and updates this result when new measurements are available. The update operation takes into the account the uncertainty in the measurements using a sensor model and employs Bayes’ rule to combine measurements and predictions. The transition model is a probabilistic model that describes how the system evolves during time, that is given the current state predicts the future state of the system. The sensor model is the likelihood of a measurement, given the state of the system.

In the UAV search operation, the state of the system to be estimated is the position (and velocity) of the target. The probabilistic transition model is expressed by $p(x(t) \mid x(t-1))$, i.e. the conditional probability distribution of the state of the target $x$ at time $t$, given its earlier state $x(t-1)$. The probabilistic sensor model, is expressed by $p(z(t) \mid x(t))$, i.e. the likelihood of an observation given a particular target position $x(t)$.

Sensor observations are assumed to be available at discrete time-points. Hence, time can conveniently be modeled as a discrete, monotonically increasing sequence $t = \{t_0, t_1, \ldots\}$. A time dependent variable $\phi(t)$ at time $t = t_k$ is denoted by $\phi_k$ and $\phi_{0:k}$ denotes the set $\{\phi_0, \phi_1, \ldots, \phi_k\}$. Using this notation, the transition model can be written by $p(x_k \mid x_{k-1})$ and the sensor model by $p(z_k \mid x_k)$. We are usually interested in the position of the target, given the sequence of observations $z_{1:k}$, i.e. $p(x_k \mid z_{1:k})$.

Theoretically, this probability density function can be estimated in two stages: prediction and update. The prediction stage means that in each time step, the conditional probability of the current position of the target given all earlier observations is calculated

$$p(x_k \mid z_{1:k-1}) = \int p(x_k \mid x_{k-1})p(x_{k-1} \mid z_{1:k-1})dx_{k-1}. \quad (2.1)$$

In the update stage, the latest observation $z_k$ is also incorporated into the calculation

$$p(x_k \mid z_{1:k}) = \frac{p(z_k \mid x_k)p(x_k \mid z_{1:k-1})}{p(z_k \mid z_{1:k-1})}. \quad (2.2)$$

If the transition model and the sensor model are linear and the process noise has a Gaussian distribution, which is a rather restrictive constraint, these calculations can be performed analytically by using a Kalman Filter, otherwise some approximate method such as Particle filters can be used [26].

2.1.3 Sequential Monte Carlo Method (Particle Filters)

Sequential Monte Carlo (SMC) method also known as Particle filters is an approach for estimating the state of a non-linear system with a non-Gaussian process noise,
using a sequence of noisy measurements [27]. SMC is a Monte Carlo approximation of the recursive Bayesian estimation approach and is based on point mass (or particle) representation of probability [26].

In the SMC method, the probability density function of the system being in state $x$, in each time-step $t_k$ is represented as a set of $n$ particles $p_k = \{(x^i_k, w^i_k)\}_{i=1}^n$, where $x^i_k$ is a point in the state-space and $w^i_k$ is the weight associated with this point at time $t = t_k$. These weights are non-negative and sum to unity.

The SMC method starts with sampling a set of $n$ particles, $S_0 = \{(x^i_0, w^i_0)\}_{i=1}^n$ from the initial distribution $p(x_0)$, such that the number of particles in each interval $[a, b]$ is proportional to $\int_a^b p(x_0)dx_0$. The weights of the particles are set equally to $1/n$. At each iteration, particles in the set $S_{k-1}$ are propagated using the transition model, that is by sampling from $p(x^i_k \mid x^i_{k-1})$. When new observations arrive the weights are updated according to $w^i_k \propto w^i_{k-1}p(z_k \mid x^i_k)$, where $z_k$ is the observation at time $t = t_k$ and $p(z \mid x)$, is the sensor model.

Particles are resampled periodically considering their weights, i.e. they will be sampled with replacement in proportion to their weights and weights are reset to $w^i_k = 1/n$ to avoid degeneracy of the algorithm [26].

When the SMC method is applied to search applications, the transition model is based on the properties of the target, terrain characteristics and other forehand information we have about the mission of the target. The sensor model is derived from the characteristics of the sensors and the signature of the target [27–29].

Here, we present briefly how we have implemented the SMC method in the UAV path planning. The method starts with sampling $S_0 = \{(x^i_0, w^i_0)\}_{i=1}^n$ randomly from the a priori information $p(x_0)$, such that the number of particles on each road segment is proportional to the probability of existence of the target on that segment. Each particle is assigned a velocity randomly sampled from the distribution of the target’s velocity and the weight of each particle is set equally to $1/n$.

At iteration $k$, particles in the set $S_{k-1}$ are propagated forward, that is the new state of the particles are calculated using their current location, velocity and a process noise based on the transition model, which also takes into account that the target is bound to the road network.

After the propagation the weights of the particles are modified depending on the sensor observation and according to the sensor model. A sensor signal in a point increases the importance (weights) of the particles near that point. On the contrary, lack of sensor signals decreases the weights of the particles which are near the sensor. After modifying, the weights are normalized.

### 2.1.4 Path Selection Criteria

As a criteria to differentiate between UAV paths, we investigate to what degree different paths decrease the uncertainty about the location of the target. We consider a path that reduces the amount of uncertainty by a higher value as a “better” one.
Information entropy [30], which is a measure of uncertainty associated with a discrete random variable $X \in \{x_1, x_2, \ldots, x_n\}$ is defined as

$$H(X) = -\sum_{i=1}^{n} p(x_i) \log_2 p(x_i).$$  \hspace{1cm} (2.3)

$H(X)$ takes only non-negative values, where 0 indicates no uncertainty and larger values correspond to higher uncertainty.

We propose the expectation of the information entropy, $E[H(X)]$, as a measure for comparing candidate UAV paths. In each step, the path that most decreases the expectation of the information entropy is selected. The SMC method, which estimates the location of the target with a set of particles, provides an appropriate mechanism to estimate the expectation of the information entropy. For example,

Consider a UAV at point A in Figure 2.1(a). The UAV has two options: path ABC, or ADE. The current estimate of the location of the target is shown by particles on these road segments.

Although the total probability of finding the target on road ABC is 0.6, the most favorable path for the UAV is ADE. After the first move, the probabilities are modified as shown in Figures 2.1(b) and 2.1(c). Thus, the expectation of the information entropy by selecting path ABC is much higher than choosing path ADE. See equations (2.4) and (2.5) in which the probability of the target being in
a road segment $XY$ is denoted by $p_{XY}$.

$$E[H(path = ABC)] = 0 \times p_{ABC} + (1 - p_{ABC})(-p_{AD} \log_2 p_{AD} - p_{DE} \log_2 p_{DE}) = 0.4(-0.5 \log_2 0.5 - 0.5 \log_2 0.5) = 0.4,$$

(2.4)

whereas,

$$E[H(path = ADE)] = 0 \times p_{ADE} + (1 - p_{ADE})(-p_{AB} \log_2 p_{AB} - p_{BC} \log_2 p_{BC}) = 0.6(-0.08 \log_2 0.08 - 0.92 \log_2 0.92) = 0.24.$$

(2.5)

Hence, it is preferable to traverse path $ADE$ first. The reason is that if the UAV fails in its first move, the situation in Figure 2.1(c) is much more favorable than Figure 2.1(b), i.e. the uncertainty about the position of the target will be less.

### 2.2 Assignment of Business Processes

Papers 4, 5, 6 and 7 in part II of this thesis address assignment of business processes to agents. In contrast to the papers related to UAV path planning that aim to develop an automated UAV search system, the goal of these papers is to develop methods for a DSS that suggests a solution to a decision maker.

Business processes are often characterized by imperfect information. The imperfectness of information may be due to both impreciseness and uncertainty. For example, assessment of capabilities of personnel is often imprecise and approximate, while the inter-arrival time of orders, which is best modeled by a probability distribution is (irreducible) uncertain information.

Business processes may be optimized in different ways. Here, by optimization of a business process, we mean assigning tasks to employees that are most qualified for those tasks. The problem consists of different sub-problems. We have chosen to address these sub-problems:

1. Estimating performance of a business process model: We provide a measure of performance of a business process based on value added by employees to the process. This model considers employees as independent agents and does not take into account the effect of interaction between them.


3. Optimization of task assignment to collaborating agents: Here, we also consider the interaction between agents and propose a method for optimization of assigning tasks to teams of agents.

4. Modeling the performance of a team of agents: We propose a model for estimating the performance of a team and discuss how different collaboration strategies of agents affect the performance of a team.
2.2.1 Estimating Performance of a Business Process Model

The aim of business process modeling is to model the steps, participants, decision logic and other features of the process relevant to the application area. Several modeling methodologies are available that model and analyze different aspects of business processes. In recent years, Business Process Modeling and Notation (BPMN) [31] has been acknowledged as a de facto standard for modeling business processes [32–34]. The current version of BPMN is 2.0. The graphical notation of BPMN is similar to a flowchart diagram; however BPMN offers a much richer set of modeling constructs. One of the strengths of BPMN is that it allows extending standard BPMN elements with additional attributes, which can be used to add non-standard elements and attributes to satisfy a specific requirement. For example, Magnani and Montesi extend BPMN to evaluate the (monetary) cost of BPMN diagrams [35]. We have extended the BPMN with the concept of agents possessing capabilities and cost attributes. Tasks are also extended with the concept of weight associated with each required capability.

We define value added by agents to a process as improvement in the quality of the output of a business process. It is assumed that a business process in which human resources perform tasks that best fit their capabilities can produce high-quality outputs. The value added to a process is the (weighted) sum of values added to tasks, which depends on to what degree tasks are assigned to employees with the right capabilities. For each task, value added is defined to be the amount of the qualified work of agents expressed in a monetary value, i.e. how much value is added to the final output of the process if the task is performed by a “sufficiently” qualified agent. Value added per time unit is defined accordingly.

Consider a process consisting of \( s \) tasks for which we distinguish totally \( n \) significant capabilities. If we have \( m \) agents, the capability matrix is defined as 
\[
C = [c_{ij}]_{m \times n},
\]
where \( c_{ij} \) is capability \( j \) of agent \( a_i \). In the same way, the weight matrix is defined as 
\[
W = [w_{jl}]_{n \times s},
\]
where \( w_{jl} \) is the weight of capability \( j \) for task \( t_l \). Then the value added matrix \( V = [v_{il}]_{m \times s} \), where \( v_{il} \) is the value added by agent \( a_i \) to task \( t_l \) per time unit is calculated by
\[
V = CW. \tag{2.6}
\]
That is, the valued added by agent \( a_i \) to task \( t_l \) is the sum of capabilities of the agent weighted by the importance of these capabilities for the task
\[
v_{il} = \sum_{j=1}^{n} c_{ij} w_{jl}. \tag{2.7}
\]
In aggregating values added by agents to a process, the following three factors play a vital role.

1. How many times each task is performed, we denote this number by \( x_l \) for task \( t_l \).
2. The impact factor of each task on the final output of the process denoted by $q_i$.

3. The assignment of tasks to agents. We denote this assignment scheme by matrix $Z = [z_{it}]_{m \times s}$, where $z_{it} = 1$ if task $t_i$ is assigned to agent $a_i$ and 0 otherwise.

Consequently, we estimate the value added to a business process by

$$u = \sum_{l=1}^{m} \sum_{i=1}^{s} x_{lt} q_l z_{il} \sum_{j=1}^{n} c_{ij} w_{jl}. \quad (2.8)$$

Agents may also have a cost, in that case the value added should be subtracted by the cost in order to yield the net value added.

In this model agents do not interact with each other, i.e., value added by several agents performing a task is the sum of value added by each of them.

### 2.2.2 Optimization of the Performance of a Business Process

Given equation (2.8) as a model for estimating the value added to a process, one may try to optimize this value. This problem has similarities with the well-studied Assignment Problem (AP) [36], and under some constraints will be reduced to it. However, in general, it is much more complex.

In the standard AP, the number of tasks and agents are equal and the goal is to assign one task to each agent such that the cost is minimized (or the gain maximized). Although the search space is huge, there are efficient algorithms such as the Hungarian method, also known as the Kuhn-Munkres algorithm [37–39], that solve the standard AP. Some modifications of the AP can also be handled by this method. For example, if the number of agents and tasks are not equal the problem can be balanced by adding “dummy” tasks or agents. If each task $t_j$ requires $d_j$ agents, one can replicate the task $d_j$ times and treat the problem as the standard AP. The problem in which each agent may perform several tasks can also be solved by a similar method. However, the problem in which tasks may require more than one agent and agents may perform more than one task (generalized assignment problem) is NP-complete.

Assigning a business process to agents is distinguished from the traditional AP, since tasks are part of the process and may be repeated a number of times before the process is completed. This number may be deterministic, modeled as a fixed probability assigned by subject matter experts, or depend on earlier events in the process.

Two main categories of business processes are distinguished: (1) assignment-independent, and (2) assignment-dependent. In the first category, different assignments of tasks to agents do not affect the workflow of the process, while the second category contains critical tasks, which depending on who are performing them may change the workflow of the business process. For instance, the process shown in
Figure 2.2 is assignment-dependent, since the process is completed only if task 3 is sufficiently well performed, which depends on the agent it is assigned to.

![Figure 2.2: An assignment-dependent process with 3 tasks.](image)

Each of the two main categories are divided into 3 types, deterministic, Markovian, and non-Markovian processes, leading totally to 6 types of processes.

1. Assignment-independent deterministic process with a predetermined workflow. The optimal solution for this type of processes is found by using the Hungarian method in polynomial time.

2. Assignment-independent Markovian process. An analytical method is suggested, which estimates the number of times each task is performed. Thus, the problem is reduced to type one and can be solved using the Hungarian method.

3. Assignment-independent non-Markovian process for which we use a simulation method to estimate the expected values of the number of times each task is performed. These values are used to find the optimal solution.

4. Assignment-dependent deterministic

5. Assignment-dependent Markovian

6. Assignment-dependent Non-Markovian
   In all three cases above, the process contains critical tasks, which may affect the workflow. We introduce two algorithms for these type of processes. The first one finds the optimal solution, but is feasible only when the number of critical tasks is few. The second algorithm is even applicable to rather large number of critical tasks, but only provides a near-optimal solution. In this algorithm a hill-climbing heuristic method is combined with the Hungarian method and simulation to find an overall near-optimal solution for assignments of tasks to agents. The Hungarian method always finds the optimal
assignment for non-critical tasks and the heuristic method tries to find near-optimal assignments for critical tasks. Both the optimal and near-optimal algorithms employ simulation in order to deal with the uncertainty in the system.

### 2.2.3 Optimization of Task Assignment to Collaborating Agents

The standard AP can be considered as a business process model in which each task is performed by one agent and only once. Processes discussed in papers 4 and 5 in part II, differ from the AP, since their tasks are part of a business process and may be repeated several times. In paper 6, we consider a specific class of assignment problems where each task is assigned to a group of collaborating agents that work as a team. When agents collaborate with each other, the outcome of their efforts usually differs from the sum of individual agents. Thus, changing one of the group members may have a vital impact on the output of the group. As before, we assume that each agent has a set of capabilities and each task has certain requirements. However, we assume that agents in a group collaborate in a team environment and the value produced by a team is a possibly non-linear real function of its members and the task, \( f(g_{S_j}, t_j) \). Here, \( g_{S_j} \) is a team of agents which perform task \( t_j \), where the index \( S_j \) is the set of indexes of the agents. The objective is to assign agents to teams such that the total value added

\[
    u(S_1, \ldots, S_n) = \sum_{j=1}^{n} f(g_{S_j}, t_j)
\]

(2.9)

is maximized, where \( n \) is the number of tasks.

In paper 6 in part II, we propose a model for the performance of a team of agents and employ a Genetic Algorithm (GA) for finding near-optimal solutions to this class of task assignment problems.

### 2.2.4 Modeling the Performance of a Team of Agents

In paper 7 in part II, the model for estimating the performance of a team of agents, which was used in paper 6 is studied in more detail. As the earlier models, this model is based on the capabilities of the agents and importance of these capabilities for the task. During a teamwork process different interactions between agents occur and different constellations of agents are built. We call a constellation of 2 or more agents a subgroup. Inspired by [40, 41], we assume that the value added by agents consists of two contributions: (1) individual contributions, and (2) subgroup contributions.

The individual contribution is calculated by

\[
    u(\text{individual}) = \sum_{i=1}^{n} \alpha_{i} v(a_{i}),
\]

(2.10)
where \( v(a_i) \) is the value produced by the individual agent \( a_i \) in a time unit and \( \alpha_{i,i} \) is the proportion of time that the agent is working alone.

The subgroup contribution is calculated by

\[
u(\text{subgroup}) = \sum_{S \subseteq A, |S| \geq 2} \alpha_S v(G_S), \tag{2.11}\]

where \( A \) is the set of all agents in the team, \( v(G_S) \) is the value produced by the subgroup \( G_S \) in a time unit, and \( \alpha_S \) is the proportion of time that the subgroup is active.

We make the assumption that, the value produced by a subgroup is expressed as the sum of values produced by agents while they are influenced by the rest of the subgroup members,

\[
v(G_S) = \sum_{i \in S} v'(a_i, G_{S\setminus\{i\}}). \tag{2.12}\]

The function \( v'(a, G) \), which we call influence function gives the value added by agent \( a \), when it is influenced by agents in a group \( G \).

We further assume that teams exhibit some degree of self-management and agents are free to select their collaboration partner during their unscheduled time. Different factors may affect the choice of agents; however, we assume that agents prefer collaborations that are most beneficial to them, i.e. increase their performance. We study the following three related issues:

1. different strategies that agents may choose for collaboration;
2. how to resolve the conflicting choices of agents;
3. the effect of the chosen strategy on the final outcome of the value produced by the team.
Chapter 3

Thesis Contribution

This chapter provides a short summary of 7 papers, which are included in part II. The thesis author’s contributions to each paper are also given.

3.1 Path Planning for UAVs Using Symbiotic Simulation


Summary

The general idea of using simulation as a method for UAV path planning in search operation is described in this paper. A framework for applying this method on UAV path planning in the search for a single ground target is introduced. To verify whether this method is feasible and to supply a tool to compare different methods a special purpose simulation tool is developed. This simulator and its features are presented in this paper.

Thesis author’s contributions

The thesis author suggested the idea of using simulation in UAV path planning and developing a framework for employing this method. The use of the SMC method for both prediction of the future state of the target and estimating the location of the target was proposed and implemented by the thesis author. A special purpose simulation tool to test and verify the algorithms was designed and implemented by the author.
3.2 Simulation-aided Path Planning of UAV


Summary

This paper focuses on a specific instance of the problem described in the previous paper. In this instance a single target is moving on a known road network, which is searched by a single UAV. It is assumed that the start point and the goal of the target are roughly known. Two methods are suggested: (1) an exhaustive search method which searches the entire road network in a manner that guarantees to find the target (albeit after a long time). The main objective of this method is to establish necessary conditions for solvability of the problem and serves as a reference for other methods; (2) a simulation based method which estimates the location of the target and prioritize road segments with higher probability of existence of the target. The simulations are performed prior to the start of the search operation and the path of the UAV once calculated is not modified.

The efficiency of the exhaustive search and off-line simulation method are tested under equal conditions using a special purpose simulation tool. The detection time is considered to be the measure of interest and is compared for these two methods.

Thesis author’s contributions

The thesis author designed the algorithms for the exhaustive and off-line simulation-aided search methods. He also suggested and designed a test case scenario for testing the performance of the methods, implemented the algorithms, and performed the test and evaluation of the methods.

3.3 Using On-line Simulation for Adaptive Path Planning of UAVs


Summary

In this paper, the on-line simulation method for UAV path planning, which was outlined in the first paper is studied in depth. The scenario is similar to the one discussed in the second paper and the results are compared with the results obtained there. The search mission is divided into a series of (coarse) time steps. In each
time step, the future location of the target is estimated by considering the initial estimation of the target and new observations. Given this estimation, different UAV paths are compared and the most beneficial one is distinguished. The path that most reduces the uncertainty about the location of the target is considered to be preferable. Hence, the expectation of information entropy as a measure for comparing different UAV paths is used in the algorithms. Among a set of UAV paths the one which has the lowest expectation of information entropy is chosen.

The performance of the on-line simulation with off-line simulation-aided path planning and the exhaustive search method is compared under equal conditions by using a special purpose simulation tool.

**Thesis author’s contributions**

The thesis author designed the algorithms for the on-line simulation-aided path planning. The idea of using the expectation of the information entropy as a measure to compare different UAV paths was proposed by the thesis author. All algorithms were designed and implemented by the author. A test case for testing and comparing the performance of the exhaustive search, off-line simulation, and on-line simulation methods was also designed and implemented by the thesis author.

### 3.4 Estimating Performance of a Business Process Model


**Summary**

In this paper, we propose a model for estimating performance of business processes by extending BPMN. This model is based on the capabilities of human resources, the importance of these capabilities for tasks, and the influence of the peripheral factors on the resources. The model can be used to compare the effect of different assignments of tasks to agents on the final output of the process. We propose an analytical method for estimating the overall performance of processes in simple cases and a simulation method, which can be used for more complicated scenarios. To illustrate how these methods work, we apply them to a business process and discuss the results.

**Thesis author’s contributions**

The thesis author proposed a set of extensions to BPMN and a model for estimating the value added by agents performing tasks. An analytical and a simulation-based method for calculating the overall performance of a business process was suggested by the author.
3.5 A Framework for Simulation-based Optimization of Business Process Models


A shorter version of this paper was published in Proceedings of the 24th ACM/IEEE Workshop on Principles of Advanced and Distributed Simulation (PADS 2010), Atlanta, GA, USA, May 17-19, 2010.

**Summary**

In this paper, we present the problem of optimizing a business process by finding the most beneficial assignment of tasks to agents. Assigning tasks in a business process to agents has similarities with the AP but is generally more complex and challenging. Six different types of processes are distinguished: (1) assignment-independent deterministic, (2) assignment-independent Markovian, (3) assignment-independent non-Markovian, (4) assignment-dependent deterministic, (5) assignment-dependent Markovian, and (6) assignment-dependent non-Markovian.

In assignment-independent processes, different assignments of tasks to agents do not affect the workflow of the process, while the assignment-dependent processes contain critical tasks, which may change the workflow of the business process depending on to whom they are assigned.

Algorithms for finding an optimal solution for the assignment-independent processes and assignment-dependent processes with a few number of critical tasks are presented. An algorithm that finds near-optimal solutions for assignment-dependent processes in the general case is presented. A software program, which is implemented to evaluate the algorithms is presented. Results of a series of tests which demonstrate the feasibility of the algorithms are included.

**Thesis author’s contributions**

The thesis author proposed categorization of business processes as described and designed (or adapted existing) algorithms to solve all categories. The author designed the software program and tests of the algorithms.

3.6 Optimization of Task Assignment to Collaborating Agents

Summary
In this paper, we consider a specific class of AP where each task is assigned to a team of collaborating agents. We assume that each agent has a set of capabilities and each task has certain requirements. We suggest a model that yields the gain when a task is assigned to a team of agents. The objective is to build teams and assign tasks to them such that the gain is maximized. We suggest a Genetic Algorithm (GA) for finding a near optimal solution to this class of task assignment problems.

We analyze the quality of the obtained solution with respect to efficiency, stability, robustness and scalability.

Thesis author’s contributions
The thesis author proposed the model for estimating the gain of assigning tasks to a team of agents.

3.7 A Model for Estimating the Performance of a Team of Agents

Summary
In this paper, we present a model for estimating the value added by a team of agents performing a task. Value added by a team is assumed to be the sum of contributions of agents while they work individually and contributions of subgroups built in the team. We assume that the value added by a subgroup is greater than the sum of values produced by individual agents, since the capability of an agent may be affected when it cooperates with agents with a higher capability. We propose a model to estimate the benefit (increase of capability) of an agent when it cooperates with other agents in a subgroup. Based on this benefit model and different (common) strategies, the agents devise plans in which they formulate to what extent they are willing to cooperate with other agents. A negotiation algorithm that resolves the conflicts between the desires of the agents is presented. The effect of this algorithm and different strategies are tested on a set of generated data.

Thesis author’s contributions
The thesis author proposed the model for estimating the benefit of an agent when cooperating with other agents in a subgroup. A model of estimation of the value
added by a team of agents performing a task was introduced by the author. Different agent strategies and the negotiation algorithm was proposed by the author. The author designed and implemented the test scenario.
Chapter 4

Conclusions and Future Work

4.1 Conclusions

In this thesis, techniques and algorithms for two types of optimization and decision making problems have been developed. The common features of these problems and the suggested solutions are: (1) The problems are complex with different aspects of imperfect information; (2) The solutions are simulation-based and combine different simulation techniques with other analytical methods and computation algorithms.

An on-line simulation-based method for UAV path planning in search operations is developed. This approach uses the SMC method to estimate the uncertain location of a target and uses simulation to distinguish the UAV path that most reduces the uncertainty about the target. Simulations are repeated periodically and the path of the UAV is modified if necessary. This general method is adapted to a scenario where a single UAV searches for a single target on a known road network. A special purpose simulation tool for testing the feasibility of the method is developed and the efficiency of the algorithm is compared with two other methods, off-line simulation-based and exhaustive search method. The results show that the on-line method is generally more efficient than the other methods.

Methods for modeling business process performance and optimization of business process assignment are discussed. A model for estimating the value added to the output of a business process is proposed. This model is based on the capabilities of agents and the importance of these capabilities for tasks in the process. The suggested model can be used as an objective function for optimization of a business process. In a business process, tasks may be repeated a number of times. This number can be a deterministic number, or a random number modeled by either a fixed or a history-dependent probability, i.e. the process is deterministic, Markovian or non-Markovian. A process may also contain critical tasks, which may change the workflow depending on to which agent they are assigned, i.e. it is assignment-dependent. If the process lacks such tasks, it is assignment-independent. We provide efficient simulation-based algorithms for optimal or near-optimal solutions for
all discussed types of processes.

A model for cooperation of agents and the value added by team of agents is presented. In this model, teams may have a degree of self-management and agents are free to choose their cooperation partner during their unscheduled time. We assume that agents prefer cooperation that increases their performance. However, this may lead to conflicting views on the extent of the cooperation. In that case, agents may use different strategies to meet each others’ demands. We propose an algorithm for resolving conflicts between agents and study the effect of the chosen strategy on the final outcome of the value produced by the team.

Although the methods proposed in this thesis require to be explored in further detail before they can be employed in real-world applications, they provide concept-level solutions for making optimal (or near-optimal) decisions for some complex problems with imperfect information:

- In the UAV search operation, two simulation-based methods are proposed and their performance is evaluated using a simulation tool developed for this purpose. While both methods are interesting, the on-line simulation method has generally a higher performance. Comparison of the detection time for this method and a case where the UAV has correct and certain information about the target, indicates that the on-line simulation method achieves a near-optimal performance in the studied scenario.

- The proposed business process optimization framework finds the optimal solution for all cases where the assignment of tasks does not change the workflow of the process. For this reason, the Hungarian algorithm is combined either with an analytical method (for Markovian processes) or a simulation method (for non-Markovian processes). For the most general cases, where the assignment of tasks may change the workflow, we propose an algorithm that finds near-optimal solutions. In this algorithm, the Hungarian algorithm is combined with hill-climbing heuristics and simulation.

- The suggested GA for assigning tasks to collaborative agents, finds solutions that are very close to the optimal one. They also deviate very little from each other. This is a measure of the stability of the obtained solutions. Furthermore, the results are not sensitive to changes in the input data, which demonstrates the robustness of the method.

- In investigating the effect of different agent strategies on the output of a team, we propose a negotiation algorithm that resolves conflicts between agents. Simulations on a set of generated data demonstrates that the performance of a team in which the members collaborate according to the Zipf’s law (principle of least effort) is near-optimal when using the suggested algorithm.
4.2 Future Work

Possible directions for future work are as follows:

- The model for estimating value added by agents to tasks is speculative and awaits further validation. It is generally very difficult to validate human performance models and even if they are validated in a specific context, it may not be the case in other domains. Being aware of this fact, we have designed our algorithms in a way that it is possible to substitute this model by more accurate models without no or little modification. However, one interesting direction is to acquire more accurate models of performance of agents in specific domains in order to validate the entire methodology.

- The model of estimating the performance of a team of agents is not incorporated in the optimization framework. Using this model in the framework is a challenging task, since optimization must occur at different levels.

- Business processes, which we study in this research are limited to a subset of all constructs in BPMN. Including the complete set of BPMN elements in the optimization framework and implemented software is another interesting, yet challenging future work.
Bibliography


