MASSPEC - MULTIAGENT SYSTEM SPECIFICATION THROUGH POLICY EXPLORATION AND CHECKING

by

SCOTT J. HARMON

B.S., Kansas State University, 2002
M.S., Kansas State University, 2004

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the
requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Computing and Information Sciences
College of Engineering

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Abstract

Multiagent systems have been proposed as a way to create reliable, adaptable, and efficient systems. As these systems grow in complexity, configuration, tuning, and design of these systems can become as complex as the problems they claim to solve. As researchers in multiagent systems engineering, we must create the next generation of theories and tools to help tame this growing complexity and take some of the burden off the systems engineer. In this thesis, I propose *guidance policies* as a way to do just that. I also give a framework for multiagent system design, using the concept of guidance policies to automatically generate a set of constraints based on a set of multiagent system models as well as provide an implementation for generating code that will conform to these constraints. Presenting a formal definition for guidance policies, I show how they can be used in a machine learning context to improve performance of a system and avoid failures. I also give a practical demonstration of converting abstract requirements to concrete system requirements (with respect to a given set of design models).

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Multiagent systems have been proposed as a way to create reliable, adaptable, and efficient systems. As these systems grow in complexity, configuration, tuning, and design of these systems can become as complex as the problems they claim to solve. As researchers in multiagent systems engineering, we must create the next generation of theories and tools to help tame this growing complexity and take some of the burden off the systems engineer. In this thesis, I propose *guidance policies* as a way to do just that. I also give a framework for multiagent system design, using the concept of guidance policies to automatically generate a set of constraints based on a set of multiagent system models as well as provide an implementation for generating code that will conform to these constraints. Presenting a formal definition for guidance policies, I show how they can be used in a machine learning context to improve performance of a system and avoid failures. I also give a practical demonstration of converting abstract requirements to concrete system requirements (with respect to a given set of design models).

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A special thanks goes to my family who have had to put up with me being a "perpetual student" and who have supported me during my late nights of research, my weekends of writing, and my conference trips.

Dedication

To my wife Lisa and children Benjamin, Teresa, Julia, Thomas, Katherine, Samuel, Bernadette, and the unnamed.

Preface

How do you distill years of work, research, study, and thought into a single document? You cannot. However, in this work, I attempt to give you a window into my adventures. This document serves as a lense into the universe that has been formed by the years of work, research, study, and thought. This lense focuses but on a small sliver. Yet, if you strain, and examine the edges, you can catch a glimpse of the rest of my universe.

Chapter 1

Introduction

Organization-based multiagent systems engineering has been proposed as a way to design complex adaptable systems [1, 2]. Agents interact and can be given tasks depending on their individual capabilities. The agents themselves may exhibit particular properties that were not initially anticipated. As multiagent systems grow, configuration, tuning, and design of these systems can become as complex as the problems they claim to solve.

1.1 Motivation

We have identified several sources of complexity in multiagent design and deployment.

The system designer may not have planned for every possible environment within which the system may be deployed. The agents themselves may exhibit particular properties that were not initially anticipated.

The system designer is faced with the task of designing a system to not only meet functional requirements, but also non-functional requirements. Conflicts within non-functional requirements should be uncovered and, if necessary, the stakeholders should be consulted to help resolve those conflicts.

Current organization-based multiagent system design documents give us a high-level abstraction of the system. This high-level abstraction can be leveraged to automate the analysis of aspects of the system with respect to the system requirements; both concrete and abstract. Abstract requirements (soft-goals) represent qualities rather than products

of the system. These qualities can often be in conflict with respect to the system design. These conflicts are usually resolved during implementation and many times in an ad-hoc manner. We bring these decisions back to design-time, before implementation begins. This allows for more realistic expectations by the stakeholders for the final product through the discussion and resolution of these conflicts early within the design process.

1.2 Thesis Statement

Guidance policies offer a useful construction for reasoning with multiagent systems and developing automated tools for aiding in their construction. Specifically, guidance policies help system designers to construct multiagent systems that are adaptable and that satisfy non-functional requirements.

In order to make an engineering discipline from the art of multiagent system construction, system designers require mathematically grounded tools. While there has been much work in processing functional or quantitative requirements, non-functional, or qualitative requirements have been lagging. The aim of this research is to push the frontier and help provide some initial groundwork for other researchers to develop theories and tools to support a multiagent system designer with these qualitative concerns.

1.3 Contributions

Policies as formal constraints have been generally difficult to write correctly and difficult to implement correctly. In order to solve this problem, I propose attacking it from two directions. First, in order to write policies more naturally, we must step back and look at the reason for the policy in the first place—that is the abstract qualities that we want our system to have. Second, we must be able to either generate an implementation that conforms to our specified policies or we must be able to test an implementation against the specified policies to ensure that they are implemented correctly. With this approach, we get additional traceability of system requirements into design decisions.

I propose a specification framework for multiagent systems, using the concept of guidance policies, to both automatically generate specific constraints for a given set of multiagent system models as well as provide an implementation for generating code that will conform to these constraints.

System designers need tools to help them produce specifications and evaluate design decisions early in the design process. The approach we are taking is to first generate a set of system traces using the models created at design time. Second, we analyze these system traces, using additional information provided by the system designer. Third, we compute a set of policies that will guide the system toward the abstract qualities desired. And, fourth, we analyze the computed policies for conflicts.

1.4 Philosophy of Approach

We strongly believe in taking a practical approach in our work. The work should have practical results that can be utilized in the field. Building tools is a very good way to ensure that our research remains practical and useful to people working in this area. We do also believe, however, that the tools and work must be firmly grounded in formal logic. This is the strong foundation that helps ensure correctness and allows us to convince ourselves and others of the properties of our work.

1.5 Overview

The rest of this thesis is organized as follows. In Chapter 2, we present some of the background in multiagent systems, multiagent system engineering, organization-based multiagent systems, and the use of policies in organization-based multiagent systems. Chapter 3 introduces and formalizes the concept of guidance polices. In this chapter we also show the usefulness of guidance policies through experimentation. Next, in Chapter 4, we develop a method to automatically learn guidance policies in order to self-tune organization-based multiagent systems. Chapter 5 presents our offline approach to automatically generating

guidance policies that are based on abstract qualities. Chapter 6 looks at conflict resolution for the automatically generated guidance policies.

Chapter 2

Background

Much work has been done in the area of multiagent systems. Specifically, policies have been examined with respect to these systems. Organizational-based multiagent systems tend to utilize policies in their design and often in their implementation.

2.1 Multiagent Systems

Multiagent systems (MAS) are composed of a group of autonomous agents. In a cooperative environment, they work together to achieve a common purpose or goal. Multiagent systems are expected to be robust, reliable, adaptive, and autonomous.

A multiagent system is made up of an environment, $\mathcal{E}$, a set of objects, $\mathcal{O}$, and a group of agents, $\mathcal{A}$. Ferber defines an agent as a physical or virtual entity, which has autonomy[3]. This agent can act in its environment and is driven by some sort of objective.

Multiple agents in a system necessarily form organizations. This may have an explicit or implicit structure. Organization-based multiagent systems leverage this organizational structure within system design.

2.1.1 Agents

Agents are a natural extension of object-oriented paradigms. Agents, unlike plain objects, have a life, that is they perform some actions. With this so-called "life", agents tend to be directed in their actions by some outside goal or events.

When we think of agents, we usually think of rational agents. Generally agents are simply machines that perceive and affect the environment. A rational agent, however, is "one that does the right thing" [4].

There are two types of rational agents. The first is purely reactive. These agents do not have autonomy and thus react in some predictable manner to events occurring in their environment. The second type of agent is autonomous. These agents have some notion of the goals that they are pursuing and have a certain freedom to decide how to behave in their environment.

2.1.2 Agents in Systems

Agents within some system generally are performing some function of the system. This function may require autonomous or simply reactive behavior. Because the agent is now part of a larger system, it must communicate and coordinate its actions with the rest of the system. This can be a non-trivial problem. We will later see how organization-based multiagent systems approach this problem by providing some structure to the interactions between agents and other parts of the system.

2.2 Organization-based MAS

Organization-based MAS have been proposed as a way of dealing with coordination, communication, and goals in a general manner without dealing with a specific agent [5]. Concepts from human organizations have been incorporated into this paradigm: *Goals*, *Roles*, *Protocols*, *Policies*, and *Ontologies*. Ferber defines a micro-macro relationship in multiagent systems where constraints and social objectives are placed on the agents from the organization and properties emerge from the organization because of the agents' actions [3].

2.2.1 Goals

Goals are objectives. In the simplest terms, a goal is a state that we desire our system to reach. A goal achievement may result in some concrete product, e.g. the achievement of a goal to publish a paper could result in a publication. Other goal achievements may be without a physical product, such as the the achievement of a goal to move from point A to point B. More abstract goals may be to avoid running into obstacles, or to be efficient.

2.2.2 Roles

Roles in the agent paradigm are modeled after roles in sociology. Roles usually come with responsibilities and privileges. They imply a social structure for communication and authority. They may also imply some sort of fitness to perform some action. Roles are often used to capture expected behavior of an agent who is playing a particular role.

2.2.3 Protocols

Protocols outline the details for interactions between agents. Normally, this is to communicate some sort of information. The information communicated may be used to aid in coordination, or simply the result of some request.

2.2.4 Policies

Policies are rules that are imposed on agents by the system designer. These rules may come from different entities (i.e. from within the agent itself, or implied by the role). The rules may be externally enforced by disallowing the forbidden action (or forcing the required one) or the agent may be sanctioned after a violation occurs.

2.2.5 Ontology

Ontologies define the vocabulary of the agents within a system and allow proper communication between agents. An ontology defines the objects and the relationships between them. When constructing policies, we need to represent relevant concepts and physical properties

of the environment. The relevant concepts and physical properties are the ones that we need to mention in our Roles, Goals, Protocols, and Policies. Having an ontology allows us to formally define the concepts, terms, and entities used within our policies.

2.3 Electronic Institutions

Electronic Institutions include all the concepts introduced in Organization based MAS, but make these concepts explicit in the environment. The organization is an entity in itself, bringing it's own goals and norms (policies). Electronic Institutions place more control with the institution than in simple agent organizations. Interactions between agents are typically controlled and the institution insures the system is driven toward achievement of its end.

2.4 OperA

Dignum introduced Organizations per Agents (OperA) in 2004 [6]. OperA describes an organizational framework for multiagent systems. There are three main models in OperA: the Organization model, the Social model, and the Interaction model. The Organization model describes the organization using four structures: the social structure, the interaction structure, the normative structure, and the communicative structure. These may generally be mapped to role structure, plan or goal structure, policy set, and protocols respectively. The Social model depicts an agent's responsibilities with respect to the organization. That is, it tracks the roles the agents are playing. The interaction model specifies how the various roles interact (what protocols are allowed and how they are used).

OperA partitions norms into three sets: Role norms, Scene norms, and Transition norms. Role norms are global norms that apply to a role that an agent may be playing. Scene norms are associated with agents playing roles during an interaction or coordination. Transition norms are enforced when an agent, playing a role, is transitioning from one interaction or scene to another. The norms in OperA are defined manually by the system architect and use the standard, "obligation, permission, and prohibition" categories. They are defined

using a set of predicates over the domain variables and functions.

2.5 $\mathcal{M}$OISE$^+$

$\mathcal{M}$OISE$^+$ is an extension of Model of Organization for multI-agent SytEms ($\mathcal{M}$OISE). $\mathcal{M}$OISE$^+$ describes three aspects for multiagent organizations: the structural aspect, the functional aspect, and the deontic aspect [7]. The structural aspect describes agents' relationships through roles and links. The functional aspect describes plans to achieve various goals. The deontic aspect describes the various policies (obligations and permissions) imposed on the agents.

The deontic aspect describes the policies in terms of obligations and permissions of roles that are played by agents. The permission and obligations are defined as a 3-tuple with the role, mission, and time constraint for the policy. A mission is a plan on how to achieve part of a goal of the system. The time constraint may be for all time or may be any time period (continuous or non-continuous). These policies must also be constructed by hand.

2.6 OMACS

Organization Model for Adaptive Computational Systems (OMACS) [1] defines the concepts and relationships between MAS concepts for the organization-based multiagent systems. OMACS is targeted toward the construction of highly adaptive and reliable multiagent systems.

2.6.1 Metamodel

The basic OMACS metamodel is given in Figure 2.1. OMACS defines standard multiagent system entities and their relationships. Agents are *capable* of playing roles. Roles can *achieve* goals. Policies *constrain* the organization. The organization (which is comprised of agents) *assigns* agents to play various roles in order to *achieve* specific goals. The organization may make these assignments through a centralized approach (a single agent makes the

assignments) or through a distributed approach.

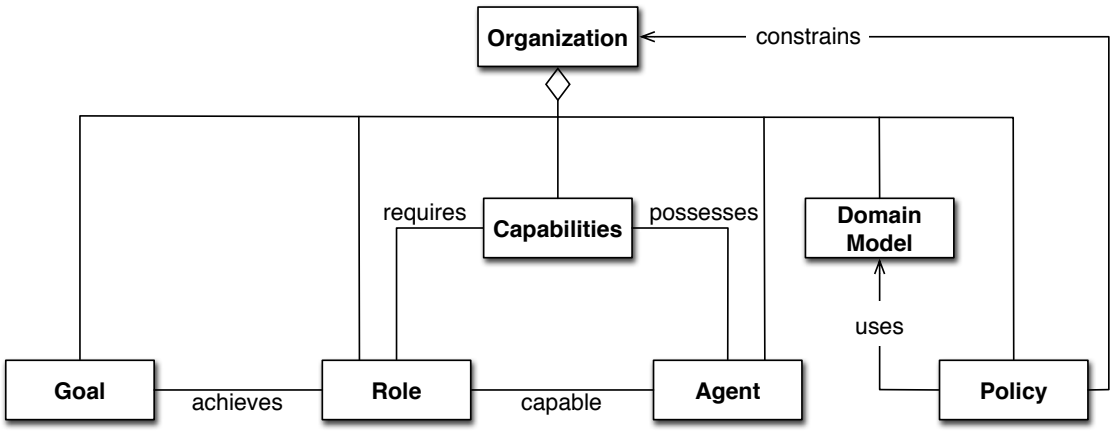


Figure 2.1: OMACS Metamodel

2.6.2 Organizational Goal Model

An important feature in both Electronic Institutions and the methodologies used to implement such systems is that of a goal model. The goal model allows for a logical decomposition of the overall goal for a system. Over time various models have been proposed.

The Goal Model for Dynamic Systems (GMoDS) [8] is one such model. This goal model is similar to the Tropos goal model [9]. GMoDS allows for such things as AND/OR decomposition of goals, as well as, *precedence* between goals and *triggering* of new goal instances (i.e. while trying to achieve a particular goal, an event may cause another goal to become active). Instance goals (triggered goals) may have parameters that specialize them for the task at hand. For example, a *Clean* goal may be parametrized on the coordinates of the area to clean.

2.6.3 Capabilities

A capability is something possessed by an agent that enables an agent to perform some function. These functions are used to achieve particular goals. In OMACS, agents may have various levels of capabilities, which determines how an agent will perform when using

each capability.

2.6.4 Agents

Agents are the entities that do things within the system. They possess capabilities, which they then can use to achieve various goals. Agents may be pursuing any number of goals at any time.

2.6.5 Roles

In OMACS, a role is defined as *"a position within an organization whose behavior is expected to achieve a particular goal or set of goals."* [1]. Roles are played by an agent when an agent is pursuing some goal. In human organizations we also have the notion of role. Various positions within a company could be considered different roles one could play within the company.

Since a role is used to achieve a goal, roles are related to the goals that they can achieve and to the capabilities that are required to play each role.

2.7 Agent Oriented Software Engineering

From these different types of agent-based systems has sprung methodologies for engineering systems based on these concepts. These methodologies give support to software engineering in building systems using agent-oriented concepts. Agent Oriented Software Engineering (AOSE) brings the science developed in agent technologies to the engineering used in practical systems.

2.7.1 Gaia

A pioneer in AOSE, Gaia [10, 11], introduced many of the concepts used today in many other AOSE methodologies. Gaia uses a series of models to move from requirements to analysis and finally to design phases. The aim of the final design is that it contain sufficient

detail to allow implementation of the system, which will properly fulfill the stakeholders' requirements. Gaia begins with a requirements statement, from there both a role model and an interaction model are constructed. From the role model, an agent model is defined. Finally, from both the role model and the interaction model, a services and an acquaintance model are designed.

Organizational rules were introduced into the analysis phase. These organizational rules are basically policies and norms over the organization as a whole. These organizational rules tend to be used to describe liveness or safety properties the system must exhibit.

2.7.2 ADELFE

ADELFE describes a methodology for building adaptive multiagent systems [12]. ADELFE is based on the AMAS Theory [13]: *"For any functionally adequate system, there is at least a cooperative interior medium system which fulfills an equivalent function in the same environment"*. The AMAS Theory proposes that a system should not be engineered, but rather the system should 'build itself' [14]. You provide the system with the desired global behavior and the ability to adapt, and the system will find the best configuration to achieve that global behavior. ADELFE consists of several workflows, moving through requirements, analysis, and design. In the requirements workflow, in addition to the normal requirements gathering, an environment model is constructed. The analysis workflow determines if the requirements can be satisfied adequately using the AMAS theory. In this workflow, agents are identified and interactions are modeled. In the design workflow, detailed descriptions of the agents are constructed using UML notation. Class diagrams of all required components are devised.

2.7.3 Prometheus

Prometheus [15] focuses on supporting the creation of systems with agents that are using the Belief, Desire, and Intention (BDI) architecture. Prometheus consists of three phases: the system specification phase, the architectural design phase, and the detailed design phase.

The system design phase is mainly a requirements gathering phase. Use cases and other methods are used to describe the system's intended functions. In the architectural design phase, the system designer identifies agents, protocols, interactions, and other design information needed to construct a system that fulfills the requirements. The detailed design phase considers the agents in more detail, describing the capabilities of the agents and how they use events and data to plan the fulfillment of the requirements.

This methodology is supported by software called the Prometheus Design Tool [16]. This tool lets a designer create graphical representations of the models and diagrams in the methodology.

2.7.4 Tropos

Many concepts in Tropos are adopted from the i^* [17] modeling framework, namely actors, goals, softgoals, and tasks. Tropos [18, 19] specifies five phases: Early Requirements, Late Requirements, Architectural Design, Detailed Design, and Implementation. Early requirements constructs a model of the current environment, with each stakeholder as an actor in the model. The stakeholder's plans, goals, and interactions are identified. In the late requirements, the proposed system is added to the model to integrate it with the current environment. The architectural design phase constructs models of the system by decomposing the functionality into subsystems, which provide the functionality needed by the particular actors identified in the early requirements phase. These subsystems are supported by new actors in the system, which will become the agents. The capabilities needed by these agents to perform the services (provide the functionality) are identified and documented. In the detailed design, "agents goals, beliefs, and capabilities, as well as communication among agents are specified in detail". Tropos uses capability, plan, and interaction diagrams to capture these details. The implementation is carried out using JACK Intelligent Agent Architecture [20]. Tropos provides a method of moving from its design documents to JACK concepts, which are used in the implementation.

Tropos is supported by the Tool for Agent Oriented Modeling for Eclipse (TAOM4E) [21]. This tool provides support for creating the various diagrams and models used by the Tropos methodology as well as some support for code generation and testing.

2.7.5 O-MaSE

Organization-based Multiagent System Engineering (O-MaSE) [22] brings the entities and relationships in OMACS and depicted in Figure 2.1 together into a set of models. These models are supported by agentTool III[1], an analysis and design tool for multiagent systems. The models we are using in this thesis are the *Goal Model*, *Role Model*, and *Agent Model*. The *Goal Model* defines the Goals of the system and their relationships as specified by GMoDS. The *Role Model* defines the Roles as well as their relationships with Goals and Capabilities. The *Agent Model* defines the Agents of the system and the relationships between Agents and Capabilities.

2.8 Policies and Norms

Following the human organization metaphor, organization-based multiagent systems often include the notion of norms or policies. While there is some disagreement to the precise definition of norms and policies, norms generally refer to conventions that emerge from society, while policies are rules imposed by an organization. Tuomela [23] defines two classes norms: rules (*r-norms*) and conventions (*s-norms*). My work is focused on rules rather than conventions. R-norms are based on agreements (or are imposed by an institution), while s-norms reflect mutual belief of the agents in a society.

Policies have been considered for use in multiagent systems for some time. Efforts have been made to characterize, represent, and reason [24] about policies in the context of multiagent systems. Policies have also been referred to as laws. Yoav Shoham and Moshe Tennenholtz [25] described *social laws* for multiagent systems. They showed how policies

[1] http://agenttool.cis.ksu.edu/

(social laws) could help a system to work together, similar to how our rules of driving on a predetermined side of the road help the traffic to move smoothly. There has also been work on detecting global properties [26] of a distributed system, which could in turn be used to suggest policies for that system. Policies have also been proposed as a way to help assure that individual agents as well as an entire multiagent system behave within certain boundaries. They have also been proposed as a way to specify security constraints in multiagent systems [27, 28]. There has been work to define policy languages by defining a description logic [29] and on the formal specification of norms [30].

Policies and norms have been used in multiagent system engineering for some time. Various languages, frameworks, enforcement and checking mechanisms have been used [24, 25, 29, 30]; however, the implementation of policies or norms in multiagent systems has been problematic. There have been many attempts at constructing elaborate enforcement mechanisms, which are often difficult to make efficient. Although multiagent systems are inherently social, most work has focused on the construction of norms for individual agents. This places a huge burden on the system architect to ensure that the global behavior of their system, given their set of norms, is suitable.

2.8.1 KAoS

In 1997, Jeffrey Bradshaw introduced the Knowledgeable Agent-oriented System (KAoS) architecture [31]. This architecture is heavily dependent on policies. KAoS uses a Defense Advanced Research Projects Agency (DARPA) Agent Markup Language (DAML) description-logic-based ontology of the computational environment, application context, and the policies themselves [29]. Policies are broken into two groups: Authorization policies and Obligation policies. Authorization policies may forbid or allow some action, while Obligation policies require some action to take place. While there can be some notion of precedence (to help automate conflict resolution), KAoS policies have not been designed with this focus. For this reason, systems that have used KAoS policies are often hard to work with due to

the verbose and cluttered policies. KAoS tends to introduce much bureaucracy to a MAS. While this is needed for very large systems, smaller to medium systems have tended to suffer from the extra work needed to maintain the bureaucracy. This is mostly due to the complexity of the runtime interpretation of the policies.

KAoS' policy-governed system is designed to work with a heterogeneous set of agents that may not be known at design-time. Policies can also be changed at runtime through an editor, which then stores the policy with the Directory Service. The Directory Service processes the policy and checks it for conflicts. If there are no conflicts, the policy is then distributed to the proper enforcement mechanisms. KAoS is also designed to cope with the possibility of malicious agents.

2.8.2 PONDER

In 2000, Ponder was introduced [32] as a language for describing various policy types:

1. Positive Authorization Policy
2. Negative Authorization Policy
3. Obligation Policy
4. Refrain Policy
5. Positive Delegation Policy
6. Negative Delegation Policy

Authorization policies give permission (or take permission) for an agent to perform some action. Obligation (or Refrain) policies create an obligation for an agent to perform (or not perform) some action. Delegation policies specify which actions can (or cannot) be delegated to other agents.

Ponder provides a policy deployment model. Policies are compiled by the Ponder compiler into a Java class. Policies are static and thus are not meant to be changed during

runtime. Ponder defines the interfaces for the enforcement agents, but does not provide an implementation. Enforcement agents typically intercept agent actions and check to make sure that they do not violate any policies.

2.9 Program Analysis

Program analysis is a growing area in computer science. The need to provide certain guarantees about software performance has increased greatly due to the use of software in so many systems. There is also a desire to automate code generation and testing that has in the past been performed by software engineers, as the cost of these engineers can be quite high. Manual code generation and testing is also error-prone; automation would greatly reduce translation, transcription, and logic errors.

Program analysis is closely related to policies and norms in multiagent systems. Program analysis can be used to ensure that software exhibits particular properties, while policies specify that multiagent systems should exhibit certain properties. There is much that can be incorporated from the world of program analysis into the area of policies in multiagent systems. Computer hardware performance has greatly increased in the past decade, which allows us to do things with software analysis and generation that was not previously feasible. Desktops of today are the super-computers of yesterday. We can now take advantage of this increased processing power to further the automation of system programming.

2.9.1 Model Checking

Model checking is one form of software analysis. In the most basic form, a model of the software system is constructed and then questions (usually in the form of some temporal logic) are asked of the system. The model checker then answers the questions about the model.

Clarke et al. [33] define three components of model checking: (1) modeling, (2) specification, and (3) verification. Modeling is the process of converting the design into a formalism

that the model checking tool can use. Specification is the task of stating properties that we want our models to exhibit. These specifications also must be in a form that our model checking tool can accept as input. Finally, verification is the process of comparing our specification to our models. This is usually done using a model checking tool.

The specification and verification are usually performed with rigorous expressions such as first order logic and proof calculus [34]. This allows the development of rules in which we may prove a program correct or incorrect with respect to the properties presented in the specification.

In order to leverage model checking and program analysis in the space of policies for multiagent systems, we extended Bogor [35] with multiagent system concepts. Bogor is an extensible, state of the art model checker.

2.10 Artificial Intelligence

Artificial Intelligence (AI) is the branch of computer science that is concerned with creating software systems that exhibit intelligence. There are many branches within AI, including speech recognition, facial recognition, and learning. AI has been described as an exercise in search.

2.10.1 Machine Learning

Machine learning is the branch of AI dealing with the assimilation of knowledge, making generalizations, and applying those generalizations to some task.

Q-Learning is a type of reinforcement learning. Reinforcement learning is learning where there is feedback in the form of some reward. This feedback reinforces outcomes that are deemed favorable. With Q-Learning, an agent learns an action-value function, which gives the expected utility of taking an action in a given state [4].

Figure 2.2 depicts a grid world in which an agent may learn the utility of moving each direction given an initial position. The squares with -1 are pits, while the square with $+1$

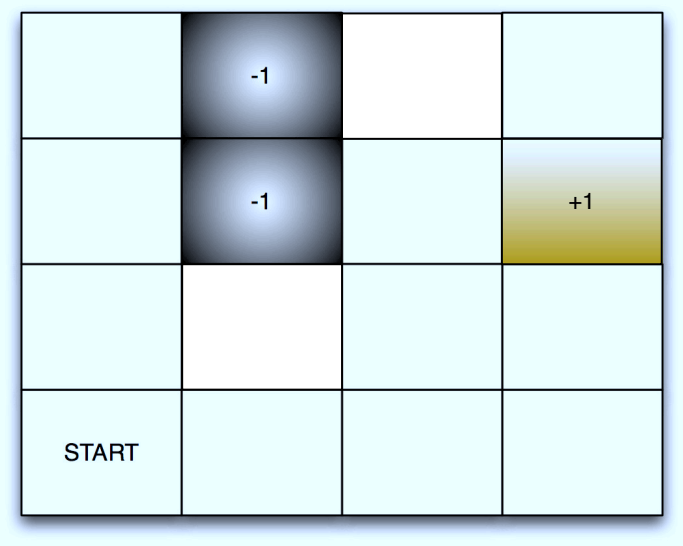


Figure 2.2: Q-Learning Grid World

is gold. In this world, an agent will learn different values for each action. This will cause it to move away from the pits and toward the gold.

While machine learning has been utilized in multiagent systems, it has not been as broadly applied to the organizational aspects of multiagent systems. While machine learning has been used at the agent and individual agent task levels directly, policies are a natural way to apply machine learning to the organizational characteristics of a multiagent systems. Policies are cross-cutting instruments, having a direct and clear effect on the overall performance of an organization.

2.10.2 Satisfiability

Satisfiability, is the general problem where one has a Boolean formula of free variables and the question is asked: "is there a set of assignments to variables that will cause the entire Boolean formula to evaluate to true?" In the general case, this problem is NP-hard [36]. For this reason, there are many algorithms that have been developed using techniques from AI to solve satisfiability problems using various heuristics in an a timely manner. The heuristics take advantage of the structure and common types of satisfiability questions that

are normally asked. As we will see later in this thesis, some satisfiability engines employ learning in the process.

Policies as a formal specification lend themselves to analysis techniques, which have been used heavily in program analysis. Satisfiability can be used to answer questions about the policies and the models that are used to create multiagent systems.

2.11 Conclusions

Multiagent systems are composed of a group of autonomous agents. In a cooperative environment, they work together to achieve a common goal. Multiagent systems are expected to be robust, reliable, adaptive, and autonomous.

Organization-based MAS have been proposed as a way of dealing with coordination, communication, and goals in a general manner. In organization-based MAS, the concepts of goals, roles, protocols, policies, and ontology are introduced. Electronic institutions take this one step further by making concrete the organization in the system as an entity itself. There are several frameworks for organization-based MAS, namely OperA, $\mathcal{M}$OISE$^+$, and OMACS. A number of software engineering methodologies have been developed to construct organization-based MAS, e.g., Gaia, ADELFE, Prometheus, Tropos, and O-MaSE.

Policies and norms have been used to constrain and form systems built using organization-based MAS software engineering methodologies; KAoS and PONDER being two popular systems. Program analysis and artificial intelligence techniques have matured in the last decade to become a viable tool in the analysis and design of these policies for large systems.

Policies have proven to be useful in the development of multiagent systems. However, if implemented inflexibly, situations such as described in [51] will occur (a policy caused a spacecraft to crash into an asteroid). For this reason, we investigate an approach using policies that will not overly constrain the system.

Chapter 3

Guidance and Law Policies

3.1 Introduction

As computer systems have been charged with solving problems of greater complexity, the need for distributed, intelligent systems has increased. As a result, there has been a focus on creating systems based on interacting autonomous agents. This investigation has created an interest in multiagent systems and multiagent system engineering, which proscribes formalisms and methods to help software engineers design multiagent systems. One aspect of multiagent systems that is receiving considerable attention is the area of policies. These policies have been used to describe the properties of a multiagent system–whether that be behavior or some other design constraints. Policies are essential in designing societies of agents that are both predictable and reliable [37]. Policies have traditionally been interpreted as properties that must always hold. However, this does not capture the notion of policies in human organizations, as they are often used as normative *guidance*, not strict *laws*. Typically, when a policy cannot be followed in a multiagent system, the system cannot achieve its goals, and thus, it cannot continue to perform. In contrast, policies in human organizations are often suspended in order to achieve the overall goals of the organization. We believe that such an approach could be extremely beneficial to multiagent systems residing in a dynamic environment. Thus, we want to enable developers to guide the system without constraining it to the point where it cannot function effectively or looses its autonomy.

3.1.1 Contributions

The main contributions of this chapter are: (1) a *formal* trace-based foundation for *law* (must always be followed) and *guidance* (need not always be followed) policies, (2) a conflict resolution strategy for choosing between which guidance policies to violate, and (3) validation of our approach through a set of simulated multiagent systems.

3.1.2 Chapter Outline

The rest of the chapter is organized as follows. In Section 3.2, we present two motivating multiagent system examples. In Section 3.3, we define the notion of *system traces* for a multiagent system, which are later used to describe policies. Section 3.4 defines *law policies* as well as *guidance policies*; we give examples and show how *guidance policies* are useful for multiagent systems and describe a method for ordering guidance policies according to importance. Section 3.5 presents and analyzes experimental results from applying policies to the two multiagent system examples. Section 3.6 concludes and presents some future work.

3.2 Motivating Examples

In order to give a clearer demonstration of the usefulness of our formalization, we present two well-known examples in multiagent systems engineering.

3.2.1 Conference Management System

A well known example in multiagent systems is the Conference Management System [38, 39]. The Conference Management System models the workings of a scientific conference. For example, authors submit papers, reviewers review the submitted papers, and certain papers are selected for the conference and printed in the proceedings. Figure 3.1 shows the complete goal model for the conference management system, which we are using to illustrate our policies. In this example, a multiagent system represents the goals and tasks

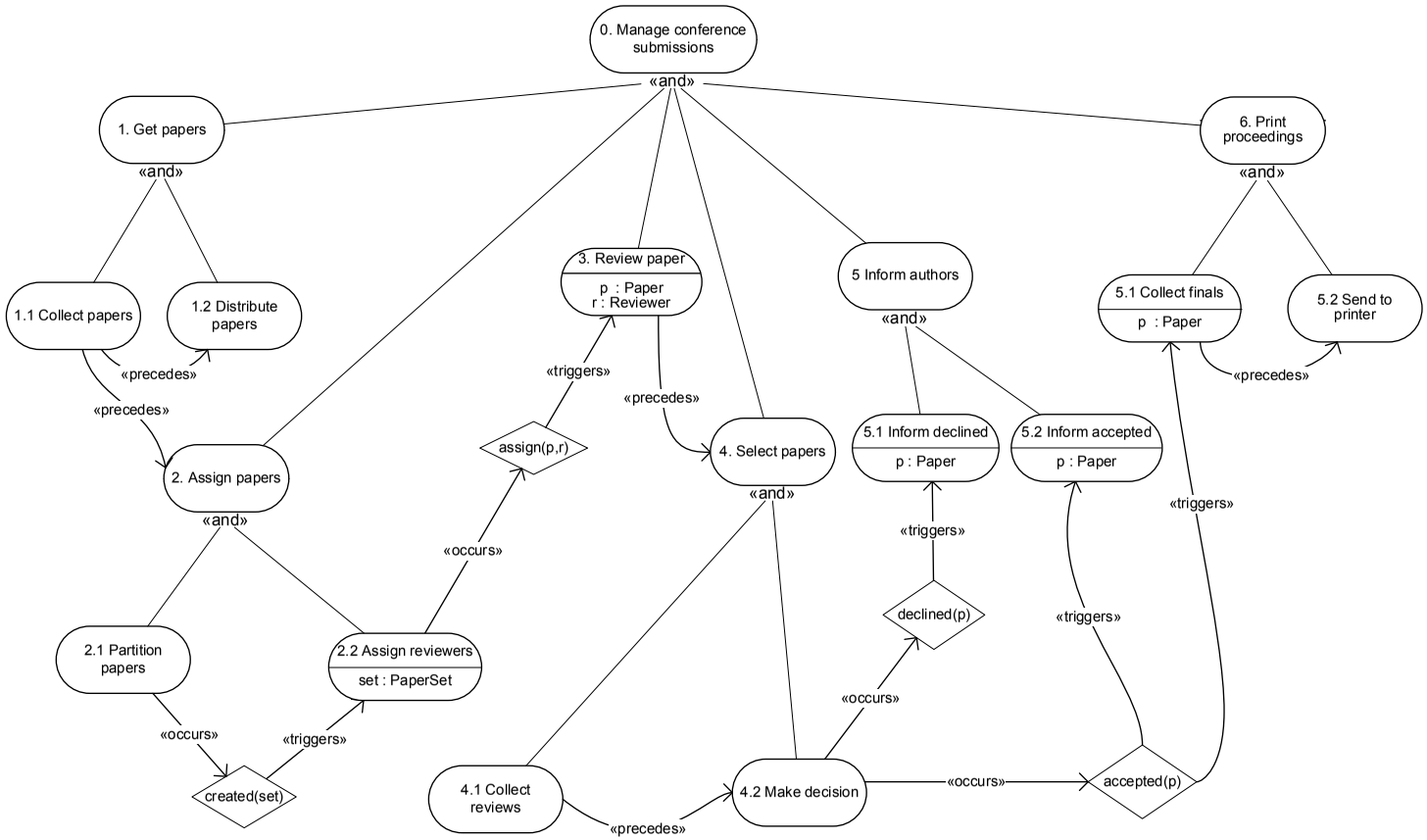


Figure 3.1: Conference Management Goal Model.

of a generic conference paper management system. Goals of the system are identified and are decomposed into subgoals.

The top-level goal, *0. Manage conference submissions*, is decomposed into several "*and*" subgoals, which means that in order to achieve the top goal, the system must achieve all of its subgoals. These subgoals are then associated through precedence and trigger relations. The *precedes* arrow between goals indicates that the source of the arrow must be *achieved* before the destination can become active. The *triggers* arrow indicates that the domain-specific event in the source may trigger the goal in the destination. The *occurs* arrow from a goal to a domain-specific event indicates that while pursuing that goal, said event may occur. A goal that triggers another goal may trigger multiple instances of that goal.

Leaf goals are goals that have no children. The leaf goals in this example consist of *Collect papers*, *Distribute papers*, *Partition papers*, *Assign reviewers*, *Collect reviews*, *Make decision*, *Inform accepted*, *Inform declined*, *Collect finals*, and *Send to printer*. For each of these leaf goals to be achieved, agents must play specific roles. The roles required to achieve the leaf goals are depicted in Figure 3.2. The role model gives seven roles as well as two outside actors. Each role contains a list of leaf goals that the role can achieve. For example, the *Assigner* role can achieve the *Assign reviewers* leaf goal. In GMoDS, roles only achieve leaf goals. The arrows between the roles indicate interaction between particular roles. For example, once the agent playing the *Partitioner* role has some partitions, it will need to hand off these partitions to the agent playing the *Assigner* role. OMACS allows an agent to play multiple roles simultaneously, as long as it has the capabilities required by the roles and it is allowed by the policies.

3.2.2 Cooperative Robotic Floor Cleaning Company

Another example to illustrate the usefulness of the concept of guidance policies is the Cooperative Robotic Floor Cleaning Company (CRFCC), which was first presented by Robby et al.[35]. In this example, a team of robotic agents clean the floors of a building. The team

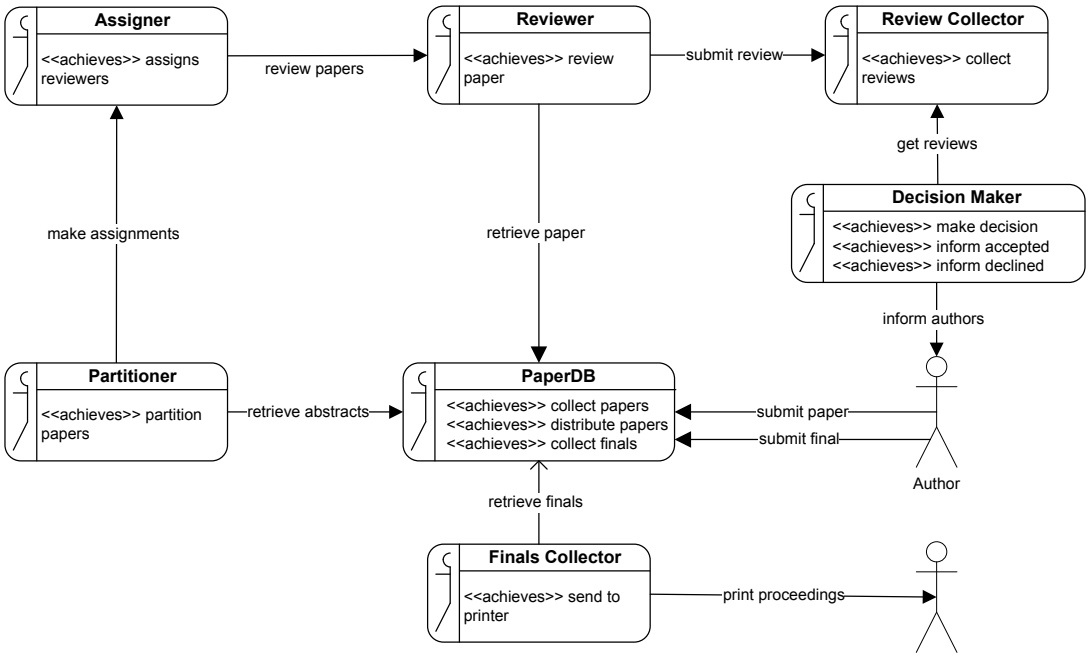


Figure 3.2: Conference Management Role Model.

has a map of the building as well as indications of whether a floor is tile or carpet. Each team member has a certain set of capabilities (e.g. vacuum, mop, etc) that may become defective over time. In their analysis, Robby et al. showed how decomposing the capabilities affected a team's flexibility to overcome loss of capabilities. We have extended this example by giving the information that the vacuum cleaner's bag needs to be changed after vacuuming three rooms. Thus, we want to minimize the number of bag changes.

Definition 3.1: Flexibility. *Flexibility is the ability of the system to reorganize to overcome individual agent failures. [35]*

The goal model for the CRFCC system is fairly simple. As seen in Figure 3.3, the overall goal of the system (Goal 0) is to clean the floors. This goal is decomposed into three conjunctive subgoals: *1. Divide area*, *2. Pickup area*, and *3. Clean area*. The *3. Clean* goal is decomposed into two disjunctive goals: *3.1 Clean tile* and *3.2 Vacuum area*. Depending on the floor type, only one subgoal must be achieved to accomplish the *3. Clean area* goal. If

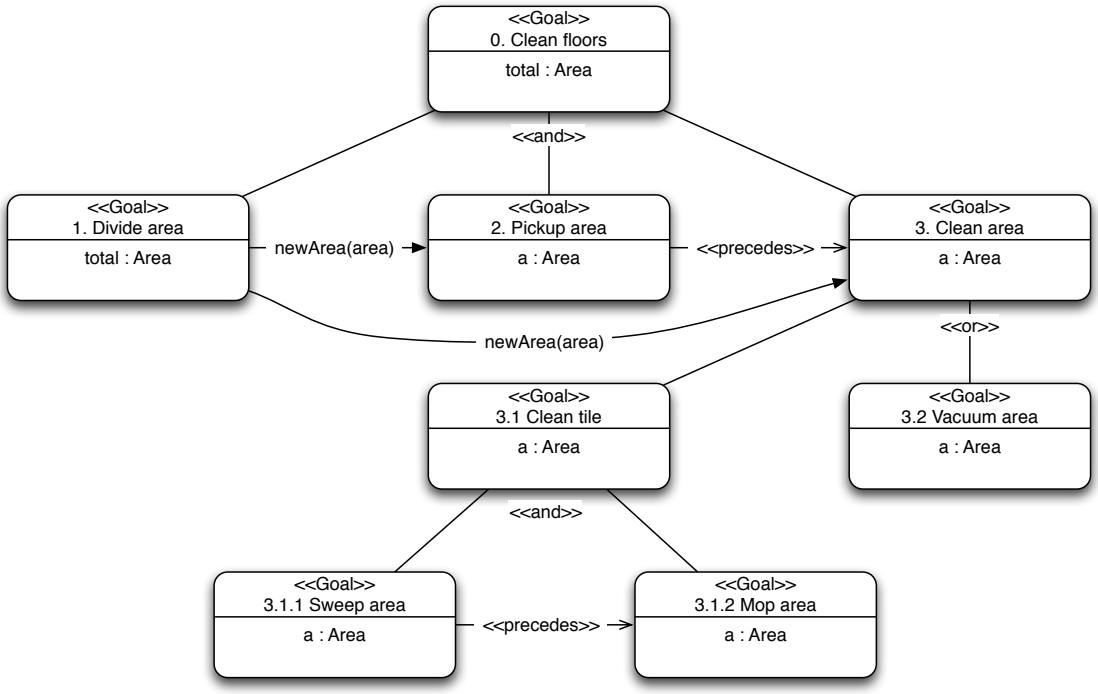


Figure 3.3: CRFCC Goal Model.

an area needs to be swept and mopped (i.e. it is tile), then goal *3.1 Clean tile* is decomposed into two conjunctive goals: *3.1.1 Sweep area* and *3.1.2 Mop area*. After an agent achieves the *1. Divide area* goal, a certain number of *2. Pickup area* and *3. Clean area* goals will be triggered (depending on how many pieces the area is divided into). After the *2. Pickup area* goals are completed, the *3. Clean area* goals will activate goals for the tile areas (*3.1.1 Sweep area* and *3.1.2 Mop area*) as well as goals for the carpeted areas (*3.2 Vacuum area*).

Figure 3.4 gives the role model for the CRFCC. In this role model, each leaf goal of the system is achieved by a specific role. The role model may be designed many different ways depending on the system's goal, agent, and capability models. Thus, depending on the agents and capabilities available, the system designer may choose different role models. For this thesis, we consider only one of these possible role models. In the role model in Figure 3.4, the only role requiring more than one capability is the *Pickuper* role. This role requires both the *search* and *move* capability. Thus, in order to play this role, an agent must possess both capabilities.

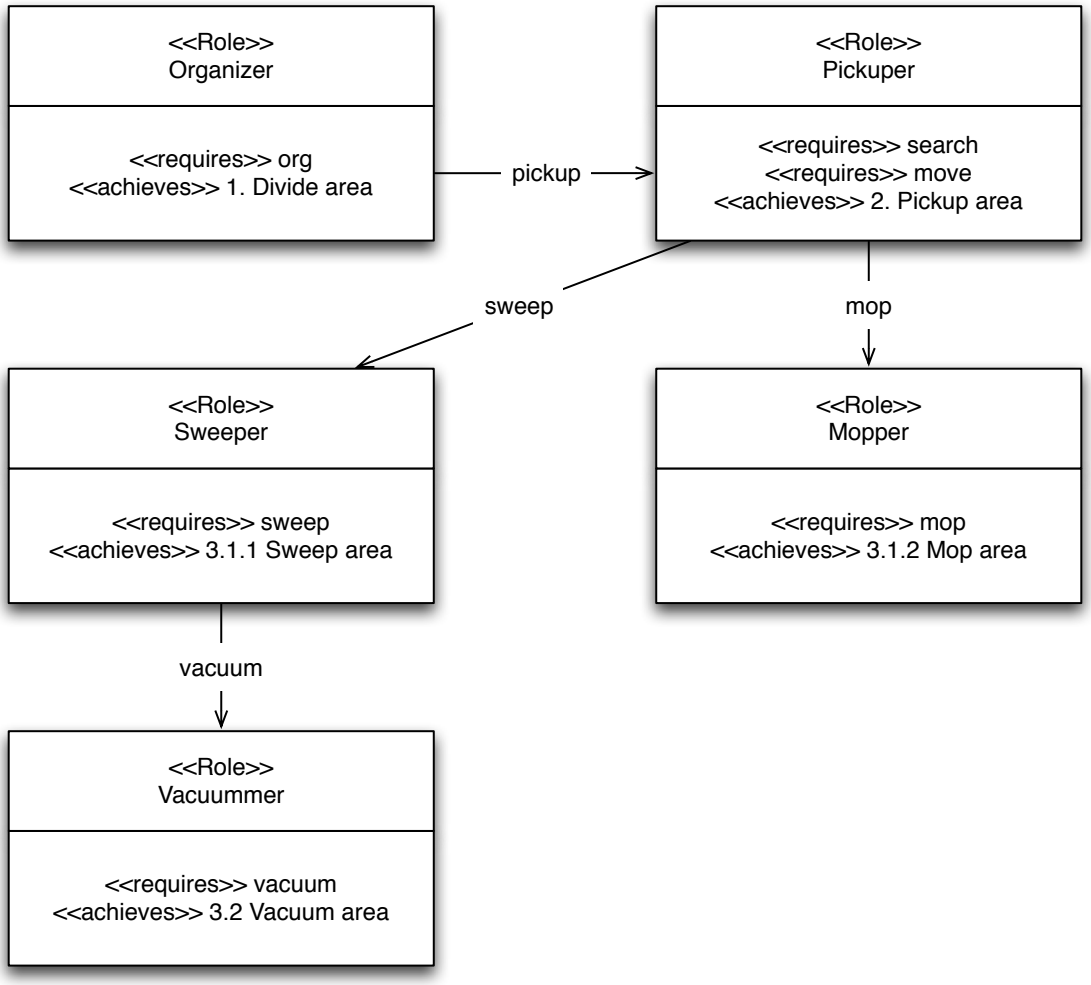


Figure 3.4: CRFCC Role Model.

3.3 Multiagent Traces

There are several observable events in an OMACS system. A *system event* is simply an action taken by the system. We are concerned with specific actions that the organization takes. For instance, an assignment of an agent to a role is a system event. The completion of a goal is also a system event. In an OMACS system, we can have the system events of interest shown in Figure 3.5a.

At any stage in system execution, there may be certain properties of interest. Some are domain-specific (only relevant to the current system), while others are general properties such as the number of roles an agent is currently playing. State properties that are relevant to the conference management CRFCC systems are shown in Figure 3.5b.

Event	Definition
$C(g_i)$	goal g_i has been completed.
$T(g_i)$	goal g_i has been triggered.
$A(a_i, r_j, g_k)$	agent a_i has been assigned role r_j to achieve goal g_k.

(a) System Events.

Property	Definition
$a.reviews$	the number of reviews agent a has performed.
$a.vacuumedRooms$	the number of rooms agent a has vacuumed.

(b) Properties

Figure 3.5: Events and Properties of Interest.

3.3.1 System Traces

In order to describe multiagent system execution, we use the notion of a system trace. An (abstract) *system trace* is a projection of system execution with only desired state and event information preserved (role assignments, goal completions, domain-specific state property changes, etc).

We are only concerned with the events and properties given above and only traces that result in a successful completion of the system goal. Let E be an event of interest and P be a property of interest. A *change of interest* in a property is a change for which a system designer has made some policy. For example, if a certain integer should never exceed 5, a change of interest would be when that integer became greater than 5 and when that integer became less than 5. Thus a change of interest in a property is simply an abstraction of all the changes in the property.

Definition 3.2: Change of interest. *A change of interest in property P is an event where the value associated with P has been updated and P is used in a policy.*

ΔP indicates a change of interest in property P. A system trace may contain both events and changes of interest in properties. Changes of interest in properties may be viewed as events, thus, for simplicity we include both and use both interchangeably. Thus, a system trace is defined as:

Definition 3.3: System trace. *A system trace is a projection of a sequence of system events with only desired state and event information preserved.*

$$E_1 \rightarrow E_2 \rightarrow \dots \tag{3.1}$$

As shown in Formula 3.1, a trace is simply a sequence of events. An example subtrace of a multiagent system, where g_1 is a goal, a_1 is an agent, and r_1 is a role, might be:

$$\dots T(g_1) \rightarrow A(a_1, r_1, g_1) \rightarrow C(g_1) \dots \tag{3.2}$$

Formula 3.2 means that goal g_1 is triggered, then agent a_1 is assigned role r_1 to achieve goal g_1, finally, goal g_1 is completed.

We use the terms *legal trace* and *illegal trace*. An *illegal trace* is an execution path that we do not want our system to exhibit, while a *legal trace* is an execution path that our system may exhibit. Intuitively, policies cause some traces to become *illegal*, while others remain *legal*.

Definition 3.4: Subtrace. *A subtrace is a subsequence of the events within a trace. E.g., if we have the trace $E_1 \rightarrow E_2 \rightarrow E_3$, then one possible subtrace is $E_2 \rightarrow E_3$.*

Definition 3.5: Legal trace. *A legal trace is a sequence of events for which no subsequence (subtrace) violates a given set of constraints.*

Definition 3.6: Illegal trace. *An illegal trace is a sequence of events in which a subsequence (subtrace) exists that violates a given set of constraints.*

We are able to use the notion of system traces because the framework we are using to build multiagent systems constructs mathematically specified models[1, 8] of various aspects of the system (goal model, role model, etc.). This can be leveraged to formally specify policies as restrictions of system traces. Now that we have a formal definition of system traces, we can leverage existing research on property specification and concurrent program analysis.

3.4 Policies

Policies may restrict or proscribe behaviors of a system. Policies concerning agent assignments to roles have the effect of constraining the set of possible assignments. This can greatly reduce the search space when looking for the optimal assignment set [40].

Other policies can be used for verifying that a goal model meets certain criteria. This allows the system designer to more easily state properties of the goal model that may be verified against candidate goal models at design time. For example, one might want to ensure that our goal model in Figure 3.1 will always trigger a *Review Paper* goal for each paper submitted.

Yet, other policies may restrict the way that roles can be played. For example, *when an agent is moving down the sidewalk it always keeps to the right.* These behavior policies also restrict how an agent interacts with its environment, which in turn means that they can restrict protocols and agent interactions. One such policy might be that an agent playing

the *Reviewer* role must always give each review a unique number. These sort of policies rely heavily on domain-specific information. Thus it is important to have an ontology for relevant state and event information prior to designing policies [41].

3.4.1 Language for policy analysis

To describe our policies, we use temporal formula with quantification similar to [42], which may be converted into Linear Temporal Logic (LTL) [43] or Büchi automata [44] for infinite system traces, or to Quantified Regular Expressions [45] for finite system traces. The formulas consist of predicates over goals, roles, events, and assignments (recall that an assignment is the joining of an agent and role for the purpose of achieving a goal 2.6.1). The temporal operators we use are as follows: $\Box(x)$, meaning x holds always; $\Diamond(x)$, meaning x holds eventually; and $x \; \mathcal{U} \; y$, meaning x holds until y holds.[1] We use a mixture of state properties as well as events [46] to obtain compact and readable policies. An example of one such policy formula is:

$$\forall a_1 : Agents, \; \mathcal{L} : \Box(sizeOf(a_1.reviews) \leq 5) \tag{3.3}$$

Formula 3.3 states that it should always be the case that each agent never review more than five papers. The $\mathcal{L}$: indicates that this is a *law policy*. The property *.reviews* can be considered as part of the system's state information. This is domain-specific and allows a more compact representation of the property. This policy may be easily represented by a finite automata as shown in Figure 3.6.

Definition 3.7: Law policy. *A Law Policy is a rule or formula that must hold true for every subtrace of our system traces.*

The use of the $A()$ predicate in Figure 3.6 indicates an assignment of the *Reviewer* role to achieve the *Review paper* goal, which is parametrized on the paper p. This automata depicts the policy in Formula 3.3, but in a manner that allows a model checker or some

[1] We only reason about bounded liveness properties because we only consider successful traces.

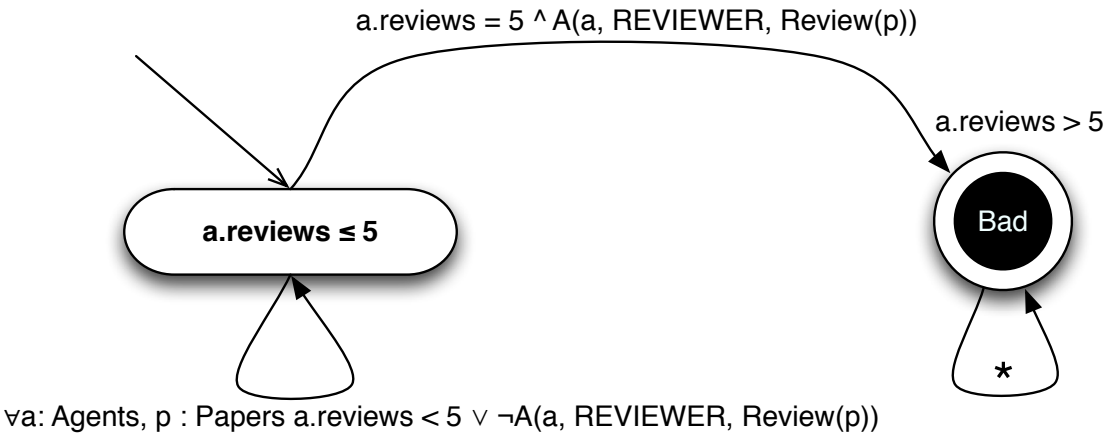


Figure 3.6: No agent may review more than five papers.

other policy enforcement mechanism to detect when violation occurs. The accepting state indicates that a violation has occurred. Normally, this automata would be run alongside the system, either at design time with a model checker [33], or at run-time with some policy enforcement mechanism [47].

We would like to emphasize here that we do not necessarily expect the designer to specify their policies by hand editing LTL. LTL is complex and designing policies in LTL would be error prone and thus could potentially mislead the designer into a false sense of security or simply to compose incorrect policies. There has been some work in facilitating the creation of properties in LTL (and other formalisms) for program analysis such as specification patterns [48]. There has also been work done to help system property specification writers to graphically create properties [49] (backed by LTL) by manipulating automata and answering simple questions regarding elements of the property.

3.4.2 Law Policies

The traditional notion of a policy is a rule that must always be followed. We refer to these policies as *law policies*. An example of a law policy with respect to our conference management example would be *no agent may review more than five papers*. This means that our system can never assign an agent to the *Reviewer* role more than five times. A law

policy can be defined as:

$$\mathcal{L} : Conditions \rightarrow Property \tag{3.4}$$

Conditions are predicates over state properties and events, which, when held true, imply that the *Property* holds true. The *Conditions* portion of the policy may be omitted if the *Property* portion should hold in all conditions, as in Formula 3.3.

Intuitively, for the example above, no trace in the system may contain a subtrace in which an agent is assigned to the *Reviewer* role more than five times. This will limit the number of legal traces in the system. In general, *law policies reduce the number of legal traces for a multiagent system.* The policy to limit the number of reviews an agent can perform is helpful in that it will ensure that our system does not overburden any agent with too many papers to review. This policy as a pure law policy, however, could lead to trouble in that the system may no longer be able to achieve its goal. Imagine that more papers than expected are submitted. If there are not sufficient agents to spread the load, the system will fail since it is cannot assign more than five papers to any agent. This is a common problem with using only law policies. They limit the *flexibility* of the system, which we define as *how well the system can adapt to changes* [35].

3.4.3 Guidance Policies

While the policy in (3.3) is a seemingly useful policy, it reduces flexibility. To overcome this problem, we have defined another, weaker type of policy called *guidance policies.* Take for example the policy used above, but as a *guidance policy*:

$$\forall a_1 : Agents,\ \mathcal{G} : \Box(sizeOf(a_1.reviews) \leq 5) \tag{3.5}$$

This is the same as the policy as in (3.3) except for the $\mathcal{G}$:, which indicates that it is a *guidance policy.* In essence, the formalization for guidance and law policies are the same, the difference is the intention of the system designer. *Law policies* should be used when the designer wants to make sure that some property is always true (e.g. for safety or security), while *guidance policies* should be used when the designer simply wants to guide the system.

Node	Definition
P_1	No agent should review more than 5 papers.
P_2	PC Chair should not review papers.
P_3	Each paper should receive at least 3 reviews.
P_4	An agent should not review a paper from someone whom they wrote a paper with.

Table 3.1: Conference Management Policies.

This guidance policy limits our agents to reviewing no more than five papers, *when possible*. Now, the system can still be successful when it gets more submissions than expected since it can assign more than five papers to an agent. When there are sufficient agents, the policy still limits each agent to five or fewer reviews.

Definition 3.8: Guidance policy. *A Guidance Policy is a rule or formula that must hold true for every subtrace of our system trace, when there is a potential system trace for which this is possible.*

Guidance policies more closely emulate how policies are implemented in human societies. They also provide a clearer and simpler construct for more easily and accurately describing the design of a multiagent organization. In contrast to policy resolution complexity of detecting and resolving policy contradictions in other methods [24], our methodology of using guidance policies presents an incremental approach to policy resolution. That is, the system will still work under conflicting policies and its behaviors are amenable to analysis, thus allowing iterative policy refinement.

In the definition of *guidance policies*, we have not specified how the system should choose which guidance policy to violate in a given situation. There are many ways these policies could be violated. We could allow arbitrary or random violation. In many cases, however, the designer has a good idea of how important each policy is relative to each other. For this we could have used some absolute scale, giving each policy an importance score. This would force a total ordering of policies, which may not always be the intent of the designer. There may be cases where one policy is no more important than another. For this reason, we

propose a partial ordering of guidance policies to allow the system designer to set precedence relationships between guidance policies.

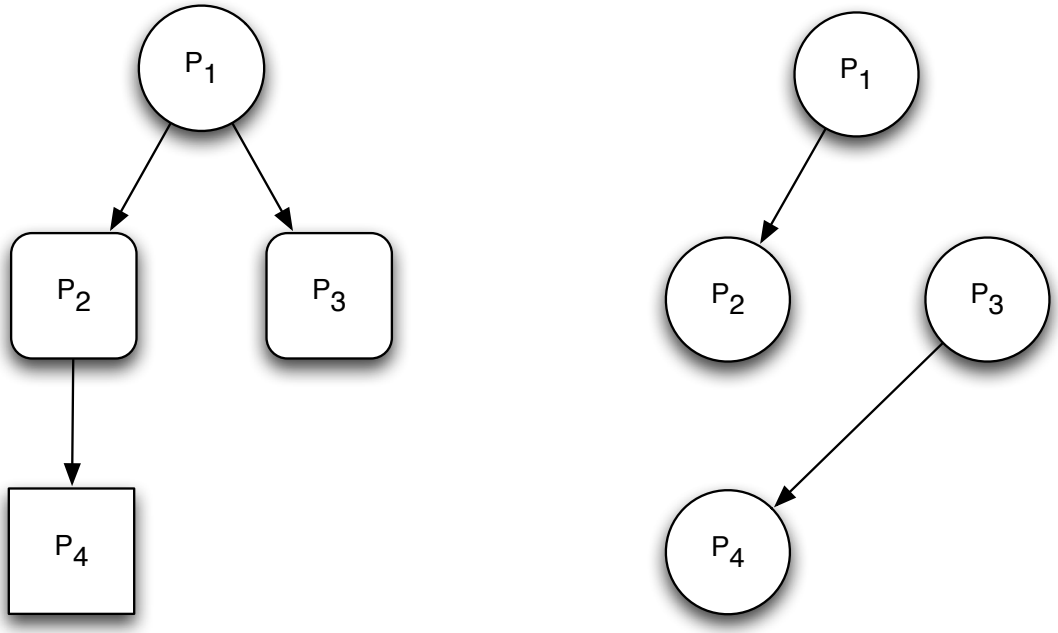
We arrange the guidance policies as a lattice, such that a policy that is a parent of another policy in the lattice, is *more-important-than* its children. By analyzing a system trace, one can determine a set of policies that were violated during that trace. This set of violations may be computed by examining the policies and checking for matches against the trace. When there are two traces that violate policies with a common ancestor, and one (and only one) of the traces violate the common ancestor policy, we mark the trace violating that common ancestor policy as illegal. Intuitively, this trace is illegal because the system could have violated a less important policy. Thus, if the highest policy node violated in each of the two traces is an ancestor of every node violated in both traces, and that node is not violated in both traces, then we know the trace violating that node is illegal and should not have happened.

Take, for example, the four policies in the Table 3.1. Let these policies be arranged in the lattice shown in Figure 3.7a. The lattice in Figure 3.7a means that policy P_1 is more important than P_2 and P_3, and P_2 is more important than P_4. Thus, if there is any trace that violates any guidance policies other than P_1 (and does not violate a law policy), it should be chosen over one which violates P_1.

When a system cannot achieve its goals without violating policies, it may violate guidance policies. There may be traces that are still illegal, though, depending on the ordering between policies.

Definition 3.9: Illegal trace wrt. guidance policies. *An illegal trace with respect to guidance policies is a trace with a set of policy violations $\mathcal{P}$, such that for every pair of traces, if the least upper bound of the policies violated in both traces, $\mathcal{P}$, is in one (and only one) of the traces.*

For example, consider the ordering in Figure 3.7a, let trace t_1 violate P_1 and P_2, while trace t_2 violates P_2 and P_3. Round nodes represent policies violated in t_1, box nodes represent



(a) Possible Partial order of Guidance Policies.

(b) Another possible ordering.

Figure 3.7: Partial orders of Guidance Policies.

policies violated in t_2, and boxes with rounded corners represent policies violated in both t_1 and t_2. Since P_1 is the least upper bound of P_1, P_2, and P_3 and since P_1 is not in t_2, t_1 is illegal.

As shown in Figure 3.7b, the policies may be ordered in such a way that the policy violations of two traces do not have a least upper bound. If there is no least upper bound, $\mathcal{P}$, such that $\mathcal{P}$ is in one of the traces, the two traces cannot be compared and thus both traces are legal. The reason they cannot be compared is that we have no information about which policies are more important. Thus, either option is legal. It is important to see here that all the guidance policies do not need to be ordered into a single lattice. The system designer could create several unrelated lattices. These lattices then can be iteratively refined by observing the system behaviors or by looking at metrics generated for a certain policy set and ordering[35]. This allows the system designer to influence the behavior of the system by making logical choices as to what paths are considered better. Using the lattice in

Figure 3.7a, we may even have the situation where P_1 is not violated by either trace. In this case, the violation sets cannot be compared, and thus, both traces are legal. In situations such as these, the system designer may want to impose more ordering on the policies.

Intuitively, guidance policies constrain the system such that at any given state, transitions that will not violate a guidance policy are always chosen over transitions that violate a guidance policy. If guidance policy violation cannot be avoided, a partial ordering of guidance policies is used to choose which policies to violate.

3.5 Evaluation

3.5.1 CRFCC

Using our CRFCC example and a modified simulator [35], we collected results running simulations with the guidance policy: *no agent should vacuum more than three rooms*. We contrast this with the law policy: *no agent may vacuum more than three rooms*. The guidance policy is presented formally in Equation 3.6.

$$\forall a_1 : Agents,\ \mathcal{G} :\Box(a_1.vacuumedRooms \leq 3) \tag{3.6}$$

For this experiment, we used five agents each having the capabilities as shown in Figure 3.8. These capabilities restrict the roles our simulator can assign to particular agents. For example, the Organizer role may only be played by agent a_1 or agent a_5, since those are the only agents with the *org* capability. In the simulation we randomly choose capabilities to fail based on a probability given by the *capability failure rate*.

Agent	Capabilities
a_1	org, search, move
a_2	search, move, vacuum
a_3	vacuum, sweep
a_4	sweep, mop
a_5	org, mop

Figure 3.8: CRFCC Agent model

For each experiment, the result of 1000 runs at each capability failure rate was averaged. At each simulation step, a goal being played by an agent is randomly achieved. Using the capability failure rate, at each step, a random capability from a random agent may be selected to fail. Once a capability fails it cannot be repaired.

Figure 3.9 shows that while the system success rate decreases when we enforce the law policy, it does not, however, decrease when we enforce the guidance policy. Figure 3.10 shows the total number of times the system assigned vacuuming to an agent who already vacuumed at least 3 rooms for 1000 runs of the simulation at each failure rate. With no policy, it can be seen that the system will in fact assign an agent to vacuum more than 3 rooms quite often. With the guidance policy, however, the extra vacuum assignments (> 3) stay minimal. The violations of the guidance policy increase as the system must adapt to an increasing failure of capabilities until it reaches a peak. At the peak, increased violations do not aid in goal achievement and eventually the system cannot succeed even without the policy. Thus, the system designer may now wish to purchase equipment with a lower rate of failure, or add more redundancy to the system to compensate. The system designer may also evaluate the graph and determine whether the cost of the maximum number of violations exceeds the maximum cost he is willing to incur, and if not, make appropriate adjustments.

3.5.2 Conference Management System

We also simulated the conference management system described in Section 3.2.1. We held the number of agents constant, while increasing the number of papers submitted to the conference. The system was constructed with a total of 13 agents, 1 *PC Member* agent, 1 *Database* agent, 1 *PC Chair* agent, and 10 *Reviewer* agents. The simulation randomly makes goals available to achieve, while still following the constraints imposed by GMoDS. Roles that achieve the goal are chosen at random as well as agents that can play the given role. The policies are given priority using the *more-important-than* relation as depicted in Figure 3.7a.

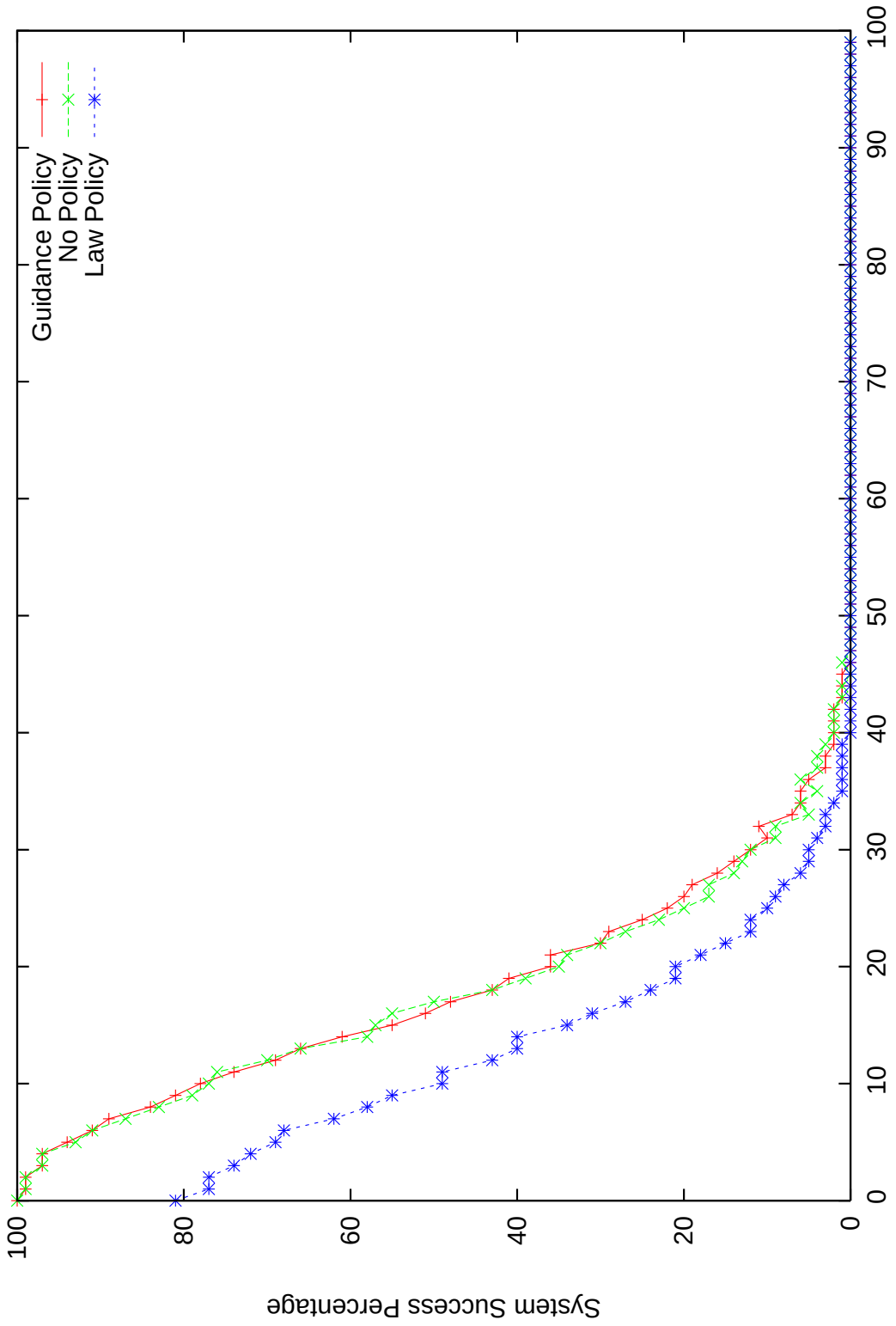


Figure 3.9: The success rate of the system given capability failure.

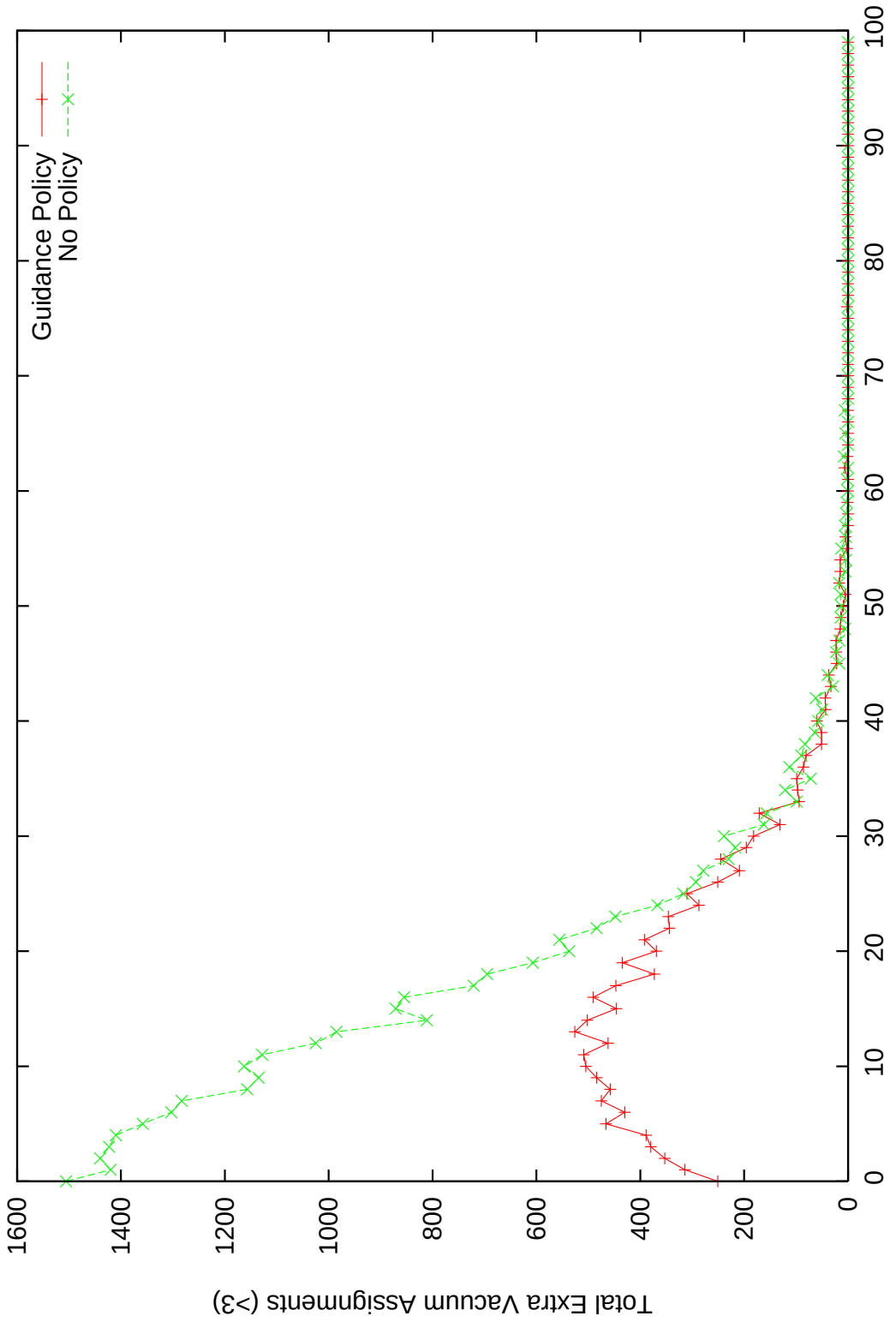


Figure 3.10: The extra vacuum assignments given capability failure.

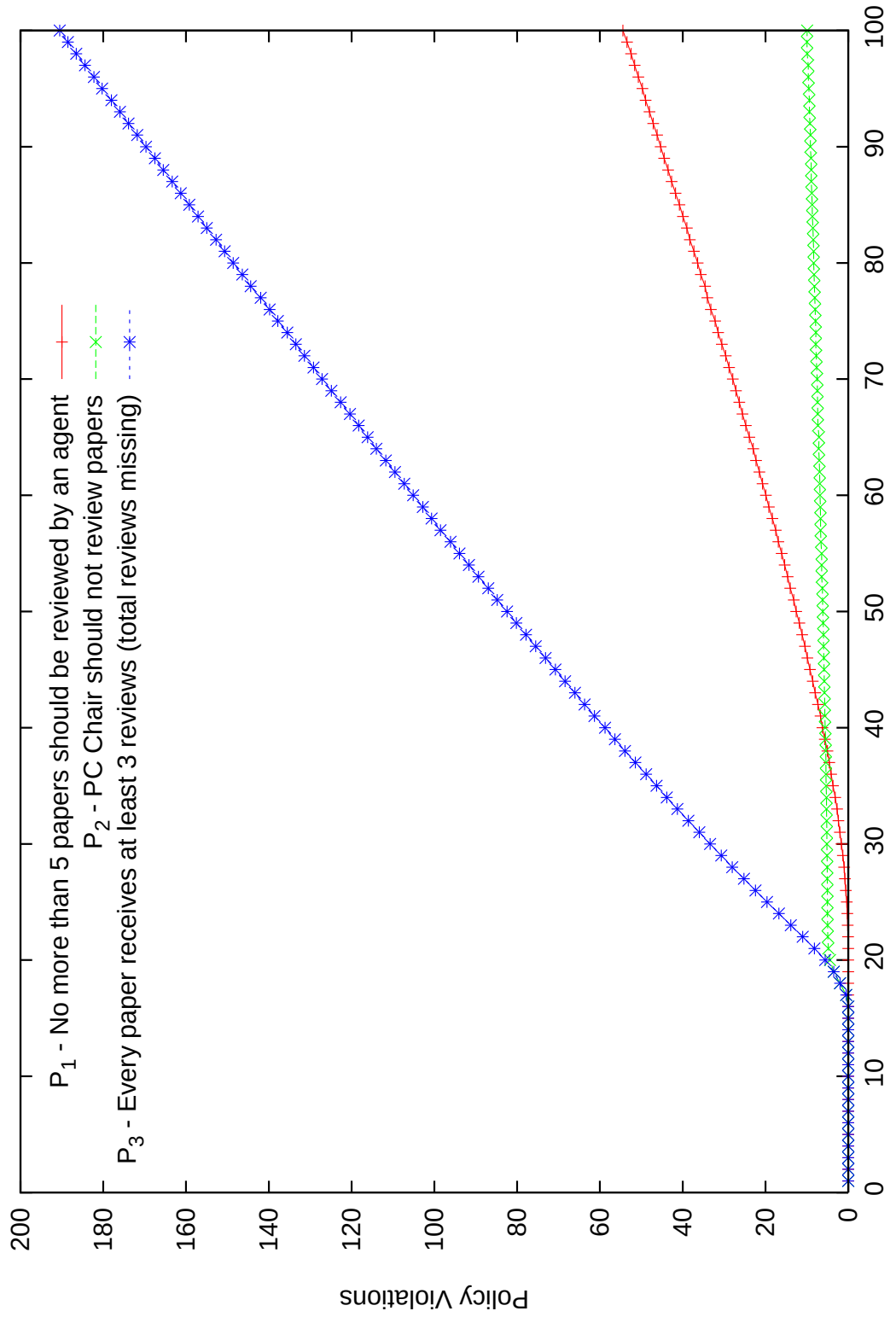


Figure 3.11: Violations of the guidance policies as the number of papers to review increases.

Figure 3.11 shows a plot of how many times a guidance policy is violated versus the number of papers submitted for review. For each set of paper submissions (from 1 to 100) we ran the simulation 1000 times and then took the average of the 1000 runs to determine the average number of violations. In all the runs the system succeeded in achieving the top level goal.

As seen by the graph in Figure 3.11, no policies are violated until around 17 papers (this number is explained below). The two least important policies (P_2 and P_3) are violated right away. The violation of P_2, however, levels off since it is interacting with P_1. The violations of P_3 are seen to grow at a much greater rate since P_3 is the least important policy.

We then changed all the guidance policies to law policies and re-ran the simulation. For 17 or more submissions, the system always failed to achieve the top level goal. This makes sense because we have only 10 Reviewer agents and we have the policies: the PC Chair should not review papers and no agent should review more than 5 papers. This means the system can only produce $5 \times 10 = 50$ reviews. But, since we have the policy that each paper should have at least 3 reviews, 17 submissions would need $17 \times 3 = 51$ reviews. For 16 or fewer papers submitted, the law policies perform identical to the guidance policies.

3.5.3 Common Results

As the experimental results in Figure 3.9 show, guidance policies *do not decrease the flexibility of a system to adapt to a changing environment*, while law policies *do decrease the flexibility of a system to adapt to a changing environment*. Guidance policies, however, do help guide the system and improve performance as shown in Figure 3.10 and Figure 3.11. The partial ordering using the *more-important-than* relation helps a system designer put priorities on what policies they consider to be more important and helps the system decide which policies to violate in a manner consistent with the designer's intentions.

3.6 Conclusions

Policies have proven to be useful in the development of multiagent systems. However, if implemented inflexibly, situations such as described in [51] will occur (a policy caused a spacecraft to crash into an asteroid). Guidance policies allow a system designer to guide the system while giving it a chance to adapt to new situations.

With the introduction of guidance policies, policies are an even better mechanism for describing desired properties and behaviors of a system. It is our belief that guidance policies more closely capture how policies work in human organizations. Guidance policies allow for more flexibility than law policies in that they may be violated under certain circumstances. In this chapter, we demonstrated a technique to resolve conflicts when faced with the choice of which guidance policies to violate. Guidance policies, since they may be violated, can have a partial ordering. That is, one policy may be considered more important than another. In this manner, we allow the system to make better choices on which policies to violate. Traditional policies may be viewed as *law policies*, since they must never be violated. Law policies are still useful when the system designer never wants a policy to be violated–regardless of system success. Such policies might concern security or human safety.

Policies may be applied in an OMACS system by constraining assignments of agents to roles, the structure of the goal model for the organization, or how the agent may play a particular role. Through the use of OMACS, the metrics described in [35], and the policy formalisms presented here, we are able to provide an environment in which a system designer may formally evaluate a candidate design, as well as evaluate the impact of changes to that design without deploying or even completely developing the system.

Policies can dramatically improve run-time of reorganization algorithms in OMACS as shown in [40]. Guidance policies can be a way to achieve this run-time improvement without sacrificing system flexibility. The greater the flexibility, the better the chance that the system will be able to achieve its goals.

Policies are difficult to write and even more difficult to conceive. For this reason, we

need to automate the process and to better aid the designer in creating guidance policies. One way to help automate this process is through the use of machine learning. In the next chapter, we show one method of using learning to automatically create guidance policies at runtime.

Chapter 4

Learning Policies to Self-Tune Systems

4.1 Introduction

As we saw in Chapter 3, guidance policies are a useful abstraction for helping us tame the autonomous nature of multiagent systems, without sacrificing the flexibility to overcome changes in the environment.

However, these policies are difficult to write and difficult to optimize for the variety of environments in which we will deploy the system. For this reason, we explore learning some of these policies during the runtime of the system.

In multiagent software engineering, agents interact and can be given tasks depending on their individual capabilities. The system designer, however, may not have planned for every possible environment within which the system may be deployed. The agents themselves may exhibit particular properties that were not initially anticipated. As multiagent systems grow, configuration and tuning of these systems can become as complex as the problems they claim to solve.

A robust system should adapt to environments, recover from failure, and improve over time. In human organizations, policies evolve over time and are adapted to overcome failures. New policies are introduced to avoid unfavorable situations. A robust organization-based multiagent system should also be able to evolve its policies and introduce new ones to avoid

undesirable situations.

Learning from mistakes is one of the most common learning methods in human society. Learning from mistakes allows one to improve performance over time, this is commonly referred to as *experience*. Experience can allow proper tuning and configuration of a complex multiagent system. In this chapter, we implement this tuning and configuration through the mechanism of organizational guidance policies.

Applying learning in multiagent systems is not new. Many authors have explored applying various learning techniques in a multiagent context [52–54]. Most of these learning applications, however, have been limited to improving an agent's performance at some task, but not the overall organization's performance. Some consider the overall team performance, but not in the structure of modern organization-based multiagent systems.

Reasoning over an entire multiagent system is a momentous task [55]. Care must be taken to ensure that learned policies do not negatively impact the organization, for example, putting the organization in a situation where it is impossible for it to complete its goal. Interactions between policies can be subtle and many hidden interactions may exist. Our use of guidance policies helps mitigate these risks substantially, thus allowing the system to experiment with different policies without the risk to the viability of the system.

4.1.1 Contributions

The main contributions of this chapter are: (1) an organizational policy-based approach to self-tuning, (2) a generalized algorithm based on Q-Learning to implement the policy-based tuning, and (3) empirical validation of our approach through a set of simulated multiagent systems.

4.1.2 Chapter Outline

The rest of the chapter is organized as follows. In Section 4.2, we present our policy learning algorithm. Section 4.3 presents and analyzes experimental results from applying our policy learning algorithm to three multiagent system examples. Section 4.4 presents some

limitations of our approach. Related work is presented in Section 4.5. Section 4.6 gives conclusions.

4.2 Self-Tuning Mechanism

An overview of how the learning takes place in our systems is given in Figure 4.1. The system first checks the goals that are available to be worked on; these goals come from GMoDS using the precedence and trigger mechanisms and support the overall goal of the system. Assignments of goals and the roles that can achieve them are given to the agents. The agents then indicate achievement failure or success. If an agent fails to achieve a goal, policies are learned over the current state knowledge. This cycles until either the system cannot achieve the main goal (system failure), or the system achieves the main goal (system success). Agents may fail to achieve a goal due to some aspect of the goal or due to some changes in the environment. The failure may be intermittent and random.

Definition 4.1: System State. *A system state is a projection of a system's history (event sequence). That is, it is a compressed (perhaps lossy) record of events in a system.*

Definition 4.2: Goal achievement failure. *A goal achievement failure is an event in which an agent decides that it can no longer complete a particular goal.*

The aim of our learning algorithm is to discover new guidance policies in order to avoid 'bad states'. Thus we generate only negative authorization policies. While the precise definition of a *bad state* is domain specific, we assume that the set of bad states is a possibly empty subset of all the states in the system. The remaining states are *good states*. Thus we have $S = S_B \cup S_G$ and $S_B \cap S_G = \emptyset$, where S is the set of all states in the system, S_G is the set of all good states in the system, and S_B is the set of all bad states in the system. Generally, bad states are states of the system that should be avoided. We use a scoring mechanism to determine which states are considered bad. The score of a state is domain

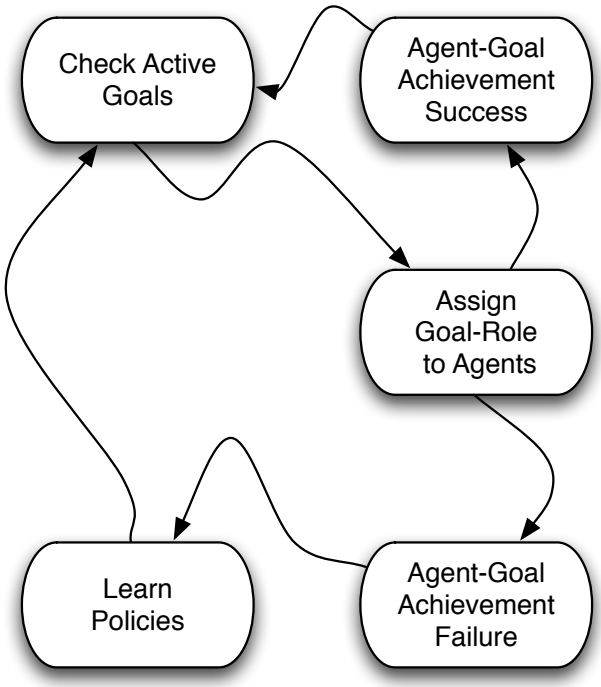


Figure 4.1: Learning Integration.

specific, however, for our experiments we used $score(S_i) = \frac{1}{1+F_i}$, where F_i is the number of agent goal achievement failures thus far in state S_i.

Definition 4.3: Negative authorization policy. *A negative authorization policy is a rule that disallows a particular action in certain cases.*

To actually generalize and not simply memorize, our learning algorithm should derive policies that apply to more than one state through generalization. In this way, the learner attempts to discover the actual cause for the bad state so that it may avoid the cause and not simply avoid a single bad state. For example, the system may detect that when the system does X, then Y, and then Z it reaches a bad state. However, this bad state may simply be a result of performing action Y and Z. Thus, we want the system to realize that it should try to avoid performing action Y and then action Z. The exact mechanism we are using will become more clear in the proceeding sections.

Our learning algorithm takes a Q-Learning [56] approach. The learner keeps track of

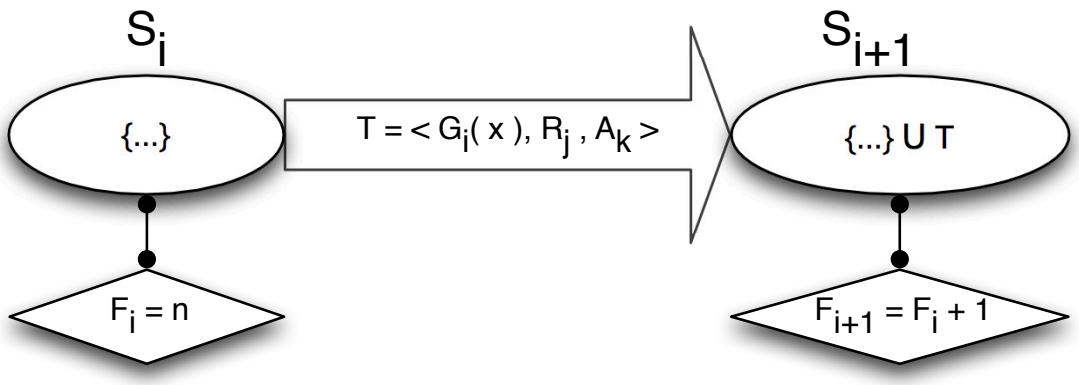


Figure 4.2: State and Action Transition.

both *bad* and *good* actions (transitions) given a state.

Definition 4.4: Bad actions. *Bad actions given a state are defined as actions that result in a state that has a score lower than the state in which the action took place.*

Definition 4.5: Good actions. *Good actions given a state are defined as actions that result in a state that has a score equal to or greater than the score of the state in which the action took place.*

The learner can then generate a set of policies that will avoid the bad states (by avoiding the bad action leading to this state). In the context of the experiments presented in this chapter, the actions considered are *agent goal assignments.*

Definition 4.6: Agent goal assignment. *An agent goal assignment is defined as a tuple,* $\langle G_i(x), R_j, A_k \rangle$*, containing a parametrized goal* $G_i(x)$*, a role* R_j*, and an agent* A_k*. The goal's parameter* x *may be any domain specific specialization of the goal* G_i *given at the time the goal is dispatched (triggered) to the system.*

Figure 4.2 shows an example state transition. In this example, state S_i is transitioning to state S_{i+1} via assignment T. In state S_{i+1} a failure occurs, thus $F_{i+1} = F_i + 1$. The state is then given a score.

Generalization of the policies is done over the state. For each action leading to a bad state, the algorithm first checks to see if we already have a policy covering this action

with the pre-state (state leading to the bad state), if so, nothing needs to be done for this bad action, otherwise we generate a policy for it. The algorithm generalizes the state by considering *matchings*.

Definition 4.7: Matching. *A matching is a binary relation between a substate and a state.* $B_k \prec S_i$*, means that* B_k *matches* S_i*.*

Intuitively, a matching occurs between a state and substate when the substate represents some part of the state. Figure 4.3 depicts the substate matching relationship. Each letter represents a *state quantum*.

Definition 4.8: State quantum. *A state quantum is the smallest divisible unit within a state.*

Definition 4.9: Unordered State. *An unordered state is a system state in which there is no ordering to the state quantum. For example, the set of current capabilities of the system can be viewed as a system state, which does not have a defined ordering.*

Definition 4.10: Ordered State. *An ordered state is a system state in which there is a defined ordering to the state quantum. For example, a history of events can be viewed as a system state in which the quanta (events), have a defined ordering.*

In the unordered state, a matching substate may consist of any subset of state quanta. In the ordered state, the order of the quanta must be preserved in the substate. The empty substate is said to match *all* states. If a state is a set of unordered quanta, $S_i = \{s_1, s_2, ...\}$, then a substate, B_k, is said to be a matching for S_i iff $B_k \subseteq S_i$. In practice, since the number of ordered states for a given system is far greater than the number of unordered states for the same system, we tend to prefer using unordered states over ordered states. Using ordered states would give the learner more information, but in the experiments we have conducted, that extra information was not worth the added state space. State space explosion with the ordered states was not offset by performance gains over the unordered

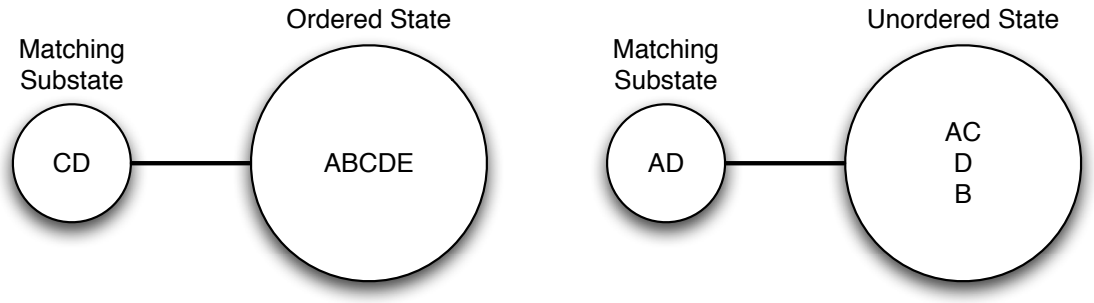


Figure 4.3: Ordered and Unordered states and their matching substates.

version. In our experiments, we used agent role-goal assignment and achievement history as our states. The quanta are the actual agent assignment tuples. A substate is said to match a state when the agent assignment tuples in the achievement and assignment sets of the substate are subsets of the corresponding sets of the state. Intuitively, substates may be seen as generalizations of states.

The operation of the algorithm is independent of the state score calculation and the substate generation. For every bad action, T, given a state, the algorithm starting with the empty substate, which matches all states, computes a score using Formula (4.1). If this score is lower than a threshold, the algorithm asks the state for the set of smallest substates containing a specific substate (initially the empty substate). Each one of these substate-action pairs, (B_k, T), are given a score,

$$score(B_k, T) = 1 - \frac{size(match_G)}{size(states_G) + size(states_B) + size(match_B)} \tag{4.1}$$

The variables in Formula (4.1) are as follows: $states_G$ is the entire set of good states given the transition T (gotten to by taking transition T); $states_B$ is the entire set of bad states given the transition T (gotten to by taking transition T); $match_G$ is, given the transition, the set of good states that the substate matches (a subset of $states_G$); and $match_B$ is, given the transition T, the set of bad states that the substate matches (a subset of $states_B$. It follows that the score is bounded as follows:

$$0 \leq score(B_k, T) \leq 1 \tag{4.2}$$

It can easily be seen that when the substate matches all good states, and we have not encountered any bad states $size(states_G) = size(match_G)$ and $size(states_B) = size(match_B) = 0$, thus $score(B_k, T) = 0$. Conversely, if the substate does not match any good states, $size(match_G) = 0$, thus $score(B_k, T) = 1$. Each substate is scored with Formula (4.1). The substate with the highest score is chosen. If this score is less than a threshold constant, the process is repeated but the substate that is given to the state to generate new substates is this maximum score substate. Thus we now build upon this substate and make it more specific.

Intuitively we start with the most general policy and then make it as specific as necessary (taking a greedy approach) so that we exclude 'enough' good states. The closer the threshold constant is to 1, the lower the possibility of the learned policies applying to good states. The closer the threshold constant is to 0, the higher the possibility that the learned policies will apply to some good states. For our experiments, we used a threshold constant of 0.6. This proved to perform sufficiently well for us since we dealt with intermittent failures. Pseudo-code for the policy generation is given in Figure 4.4.

The nature of our scoring mechanism best fits a greedy approach since we want to achieve the highest scoring trace. A random approach would not fit well here, since it would not be guided by the score. However, would could use a random approach when we are enforcing these policies. This research is outside the scope of this thesis. While lookahead could potentially improve this approach, lookahead causes an exponential increase in execution time. Because this learning algorithm is employed during runtime, an exponential increase in runtime is not practical.

Our learning employs a decay on the learned information. This is implemented by heavily favoring new information over historic information. That is, when an update is made to the score, we average the previously computed score with the new score. The new information is always makes up 50% of the new score. This allows us to adapt quickly to changes in the environment and yet not swing too wildly in the case of outlying information.

```
for all ⟨action, preStateSet⟩ in badTGivenS do
  for all preState in preStateSet do
    if !isAlreadyMatched(action, preState) then
      maxSubstate = emptySubstate
      maxScore =score(maxSubstate, action)
      done =false
      while maxscore < THRHLD∧ !done do
        substateSet =getSubstates(preState, maxSubstate)
        if substateSet = ∅ then
          done = true
        end if
        maxScore = -1
        for all substate in substateSet do
          score = score(substate,action)
          if score > maxScore then
            maxScore = score
            maxSubstate = substate
          end if
        end for
      end while
      matches = matches ∪ ⟨action, maxSubstate⟩
      policies = policies∪ generatePolicy(action, maxSubstate)
    end if
  end for
end for
```

Figure 4.4: Pseudo-code for generating the policies from the state, action pair sets.

Another approach that we tested was to avoid the bad states, that is, we ignored transitions and simply constructed policies that avoided generalizations (substates) of the bad states themselves. This alone can lead to problems. In our experiments, we found cases in which the system would live-lock. Since the learner never kept track of the event that lead to the bad state, it was possible that the learner might discover policies that forbid every agent but one from trying to achieve some goal. However, if this one agent failed with 100% probability, the system might simply reinforce that the new bad state was caused by the older decisions (substate) and would keep trying to assign the goal to the failing agent. The action-substate learner gets around this because the policies are developed for the action, if an action keeps leading to a bad state, there will be a policy discovered that forbids it. In the case where there are policies forbidding every agent from trying to achieve a goal, since we are using guidance policies, the policies will be suspended and an agent will be chosen. Eventually an agent who can achieve the goal will be chosen, and the learner will learn that that agent was not the cause of the previous failures. To avoid live-lock, we regenerate policies after every failure.

4.3 Evaluation

To test our algorithm, we simulated three different systems: a conference management system, an information system, and an improvised explosive device (IED) detection cooperative robotic system. These systems are a sampling across the usual multiagent system deployments: the conference management system is a human agent system, the information system is a software agent system, and the IED detection system is a robotic agent system. Each of these systems exhibit special tuning requirements given their different agent characteristics.

We simulated these systems by randomly choosing an active goal to achieve and then randomly choosing an agent capable of playing a role that can achieve the goal while following all current policies in the system. Active goals are simply goals that are available to be worked on. With GMoDS, a goal may become active when triggered, or when precedence is

resolved. In the case of learning, the learning code receives all events of the system. After every agent goal achievement failure, the system regenerates its learned guidance policies using all of the state, transition, and score information it has accumulated up to that point.

4.3.1 Conference Management System

Recall the Conference Management System as described in Section 3.2.1. We have modified the agents such that some of them fail to achieve their goal under certain conditions. In this system we have three types of Reviewer agents: one that never fails when given an assignment, another that fails 70% of the time after completing two reviews (*Limit Reviewer*), and the last type, that fails 70% of the time when trying to review certain types of papers (*Specialized Reviewer*). We also have the constraints that a paper must receive 3 reviews and that no reviewer should review more than 5 papers.

We used the GMoDS goal model and role model for the Conference Management system as described in Section 3.2.1. In the Conference Management system, we focused on failures of agents to achieve the *Review Paper* goal. We created the Reviewer types described above and observed the system performance. In this simulation, we varied the number of papers submitted for review to trigger the failure states. For our experiment, states contain the history of *assignments* and number of *failures* thus far. Actions are the *assignment* and *failure* events. Only leaf goals are used in assignments. Non-leaf goals are decomposed into the leaf goals.

In this experiment, we are concerned with the *Reviewer* role. Several different agent types are capable of playing this role, although they clearly behave differently.

We ran the system with no learning and recorded the number of failures. We then ran the system with the learning engaged and recorded the number of failures. Finally we ran the system with hand-coded policies that we thought should be optimal and recorded the number of failures.

The policies generated by the learner consist of forbidding an action given a state match-

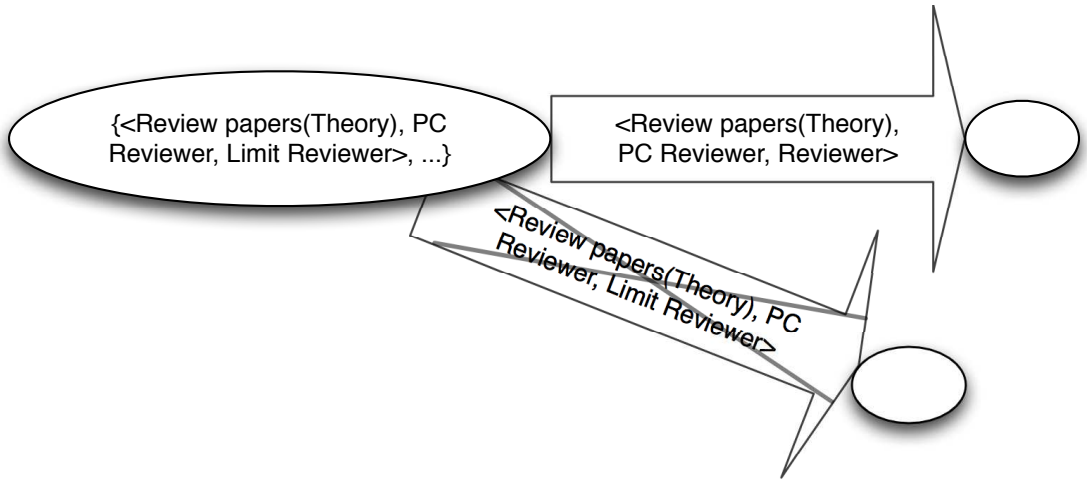


Figure 4.5: Limit Reviewer policy preventing theory papers from being assigned.

ing. For example, the learner discovered the policy: given the empty substate (meaning in any state), forbid the agent assignment ⟨*Review papers (Theory), PC Reviewer, Specialized Reviewer*⟩. Thus this policy applies to all states of the system and tries to avoid assigning theory papers to the *Specialized Reviewer*. Another policy discovered by the learner is given the substate *Assigned:*⟨*Review papers (Theory), PC Reviewer, Limit Reviewer*⟩, forbid the action ⟨*Review papers (Theory), PC Reviewer, Limit Reviewer*⟩. The learner must learn all permutations on the abstracted goal parameter. It is interesting here to note that the learner tries to forbid the *Limit Reviewer* after just one unsuccessful assignment to it. This has the added benefit that the assignment fails as late as possible, thus the system or environment could have improved before a failure occurs. The number of policies generated is relatively small, staying less than 10 in all runs. Figure 4.5 gives a graphical depiction of how a learned policy relates and is applied to the system states. From a state containing the substate, *Assigned:*⟨*Review papers (Theory), PC Reviewer, Limit Reviewer*⟩, the assignment action ⟨*Review papers (Theory), PC Reviewer, Limit Reviewer*⟩ is forbidden.

The agent type, role type, goal type, and a parameter abstraction is given. The parameter abstraction is currently domain specific, although a separate learner may categorize the parameters thus creating the abstraction function without the need for a domain expert.

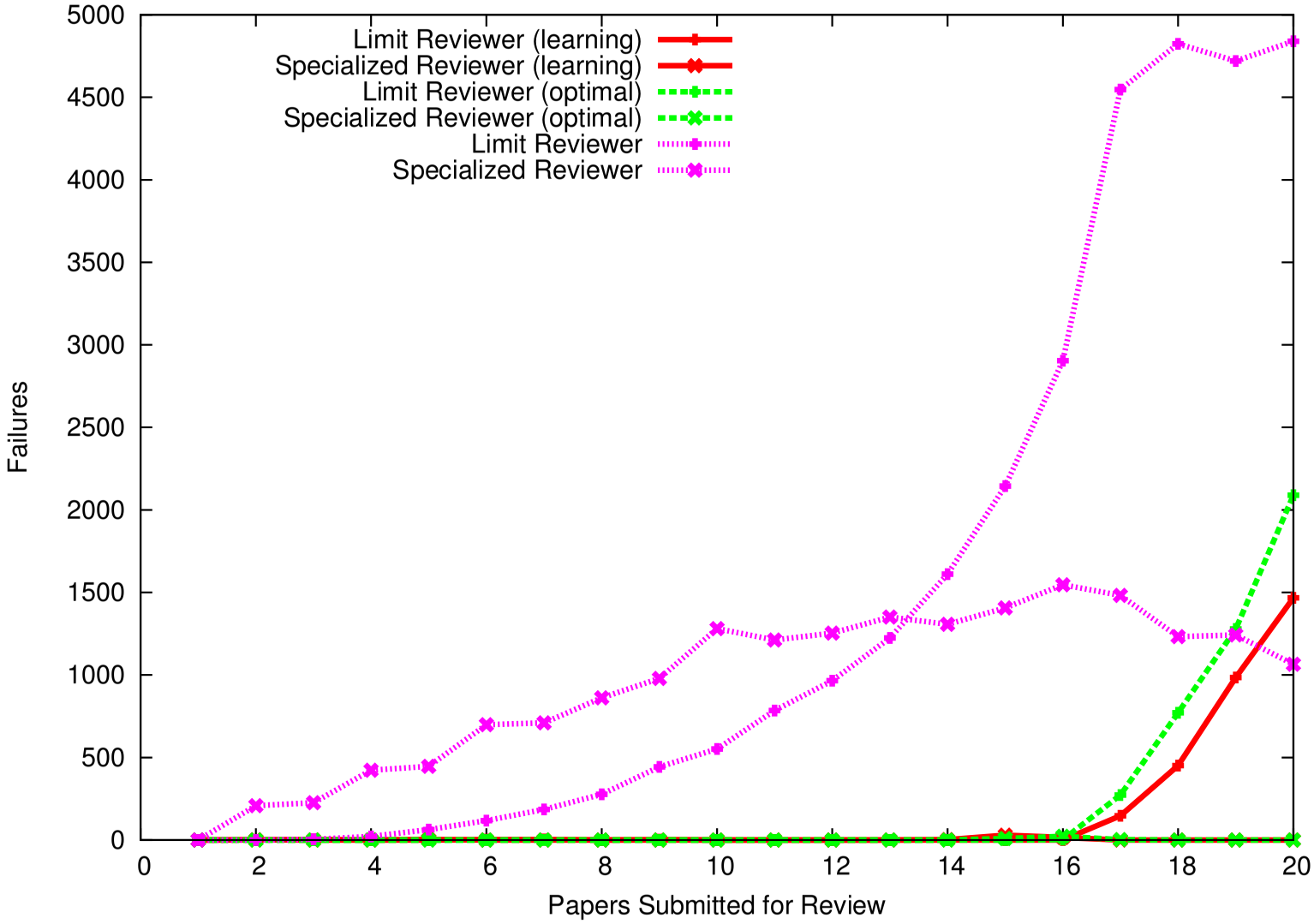


Figure 4.6: Agent goal achievement failures with self-tuning (learning), hand-tuning (optimal), and no tuning.

Figure 4.6 compares the self-tuning, learning, system to one where this learning does not occur. We also compared the learning to a system, for which, a policy expert with knowledge of the agent goal achievement failure, hand coded policies he thought would tune the system. As can be seen, our learning algorithm does no worse than the hand-coded policies, and does vastly better than a non-tuned system. The learned tuning adapts the system quickly to its deployed environment—without requiring a policy expert to analyze the specific deployment environment and hand-craft policies to tune for said environment. The sharp rise in agent achievement failures is due to the limited number of reviewer agents (10) combined with the constraints we have placed on our system (each paper must have at least 3 reviews and no agent should review more than 5 papers). There is nothing learned nor hand-coded policies can do to prevent failure due to lack of resources.

4.3.2 Information System

Another multiagent system we tested was an Information System. Peer-to-peer information gathering and retrieval systems have been constructed using multiagent systems, e.g. Remote Assistant for Information Sharing (RAIS) [57]. In our information system we had four types of information retrieval agents: *CacheyAgent*, this agent fails with a 30% probability the first time it is asked for a certain piece of information, subsequent requests for info it has retrieved previously always succeeds; *LocalAgent*, this agent fails 100% of the time when asked for remote information, otherwise it succeeds with a 100% probability; *PickyLocalAgent*, this agent fails 100% of the time on any request except for on particular piece of local data; and *RemoteAgent*, this agent fails 100% of the time on all data except for remote data.

The goal model for the Information System is shown in Figure 4.7. The leaf-goals are as follows: *1.1 Monitor Information Search Requests, 1.2.1 Perform Local Search, 1.2.2 Perform Remote Search, 1.2.3 Present Results, 2.1 Monitor Information Requests, 2.2 Retrieve Information, 3.1 Monitor for New Information, and 3.2 Incorporate new Information into Index*. This system is basically an information sharing and indexing system. Agents run

on client computers monitoring for information changes/additions as well as queries from a user. Information is indexed so that agents can quickly provide results to search queries. Search may be performed locally, or if necessary, a local agent will contact agents residing on other machines for the information.

The role-goal relation is shown in Figure 4.8. *CacheyAgent* is capable of playing roles *Local Information Retriever* and *Remote Information Retriever*. *LocalAgent* and *PickyLocalAgent* are capable of playing *Local Searcher* and *Local Information Retriever* roles. *RemoteAgent* is capable of playing the *Remote Searcher* and the *Remote Information Retriever* roles.

In this experiment, we held the agents, roles, and goals constant and recorded how the system behaved through consecutive runs. At each run, we generated 25 Information Request events. Each event randomly requested one of 4 information types, 2 local, and 2 remote. Each event also triggered a *Process Information Search* goal. We randomly assigned agents capable of achieving each active goal, while following any policy constraints. Each agent tracked the total number of goal achievement failures they had. At each run, we plotted the current total with the current run.

The system quickly learned policies restricting the *PickyLocalAgent* from various information retrieval assignments. The policies learned applied to all states (that is, they had no guard). The *LocalAgent* also became restricted from being assigned any goal with any of the various remote information, regardless of the system state. The policies concerning assignments to the *RemoteAgent* were similar to the *LocalAgent*. The *Cachey Agent*, however, was restricted by various policies, usually of the form ⟨*Retrieve Information (remote info 2), Remote Information Retriever, CacheyAgent*⟩ where agent goal assignment is forbidden given the state assignments contain ⟨*Retrieve Information (local info 1), Local Information Retriever, CacheyAgent*⟩. The learner did not have a mechanism for generating a negation policy such as "do not allow the assignment if the state does *not* match the given substate." This could be a future enhancement to the policy generation of the learning. Although the

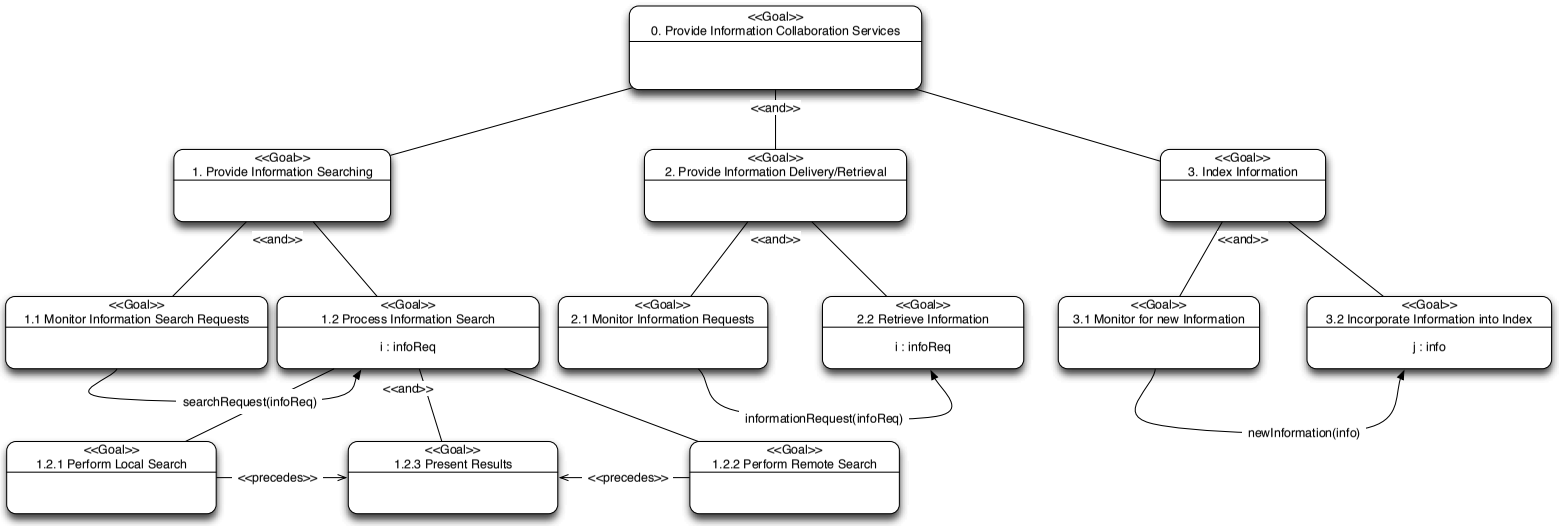


Figure 4.7: Information System Goal Model.

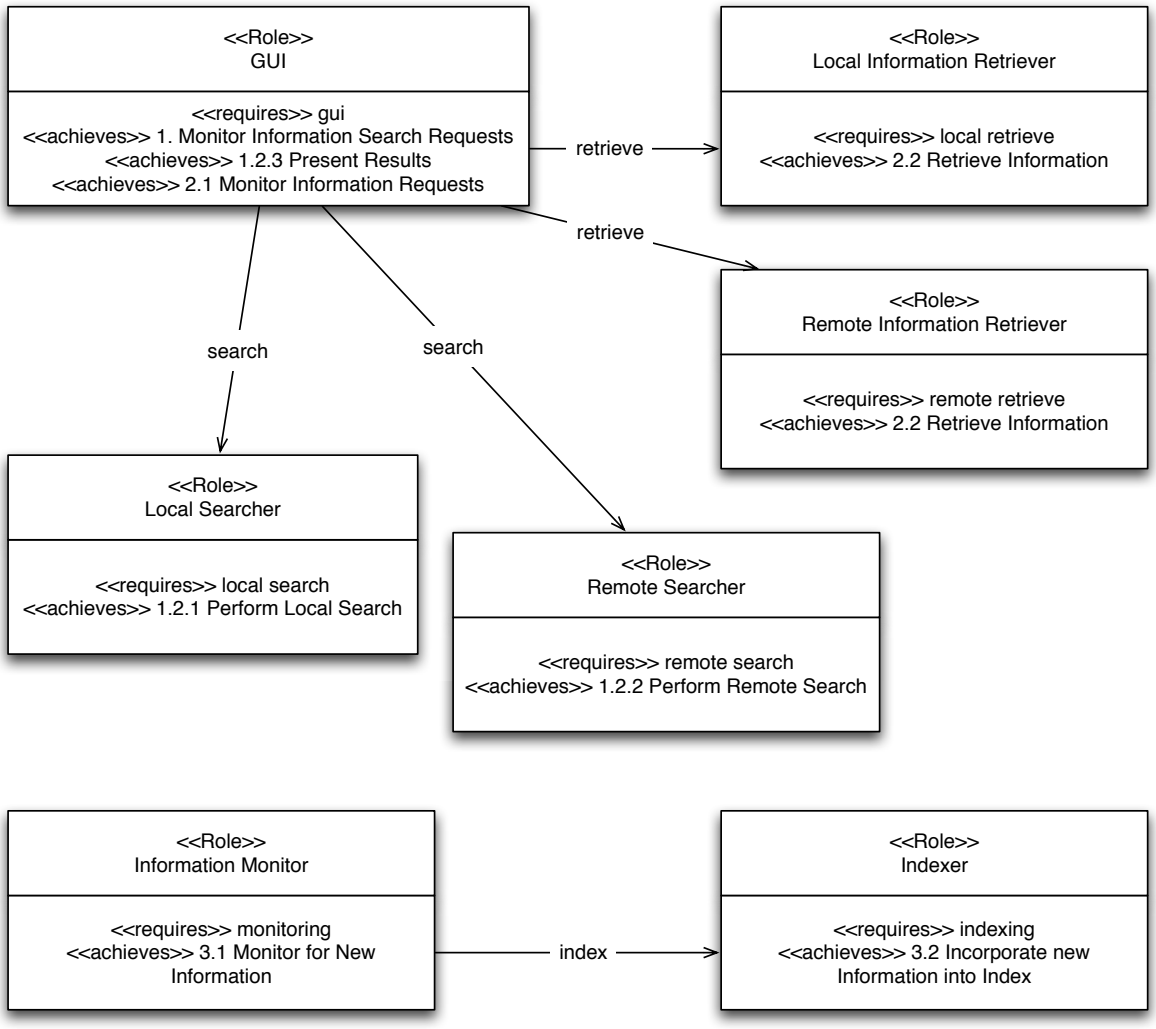


Figure 4.8: IS Role Model.

learner did not have this capability, it still managed to keep the *Cachey Agent's* failures low, and the introduction of this type of agent did not confuse the learner with regards to the type of failure of the other agents.

Figure 4.9 shows the agent achievement failures for a non-tuned system. An expert may analyze these failures and craft policies to guide the system to avoid the failures, but this would be an error-prone and tedious task. In fact, by the time a solution is proposed, the problem may well have changed.

Our self-tuning learning achieved the results given in Figure 4.10. The system was able to self-tune and adapt itself to an environment that contained multiple unique causes of failure. The adaptation happened quickly enough to greatly benefit the system.

4.3.3 IED Detection System

The use of multiagent systems in robotic teams is a natural application of multiagent systems. Unfortunately, robots and their physical environment contain more variability than purely software-based multiagent systems. System designers may not be able to plan for all this potential variability when designing their system. Capabilities of robots may vary with their physical environment. For example, a robot needing line-of-sight for communication, may go out of communication range if they move behind a physical structure in their environment. Other robots may find that they are not able to diffuse certain types of IEDs, perhaps because the IEDs are too big for the agent's grippers. Certainly, if the system designer could think of and design for all possible environmental variations, their system would be able to perform efficiently in all environments. In practice, however, this is not practical. Thus, the system should be able to automatically learn and adapt to environmental variations on its own.

In Figure 4.11 we have the goal model for the IED Detection System. The leaf goals are *Control System, Divide Area, Patrol Area, Machine Identification, Human Identification, and Defuse IED*. The overall goal of the system is to *Monitor IEDs*, this includes both

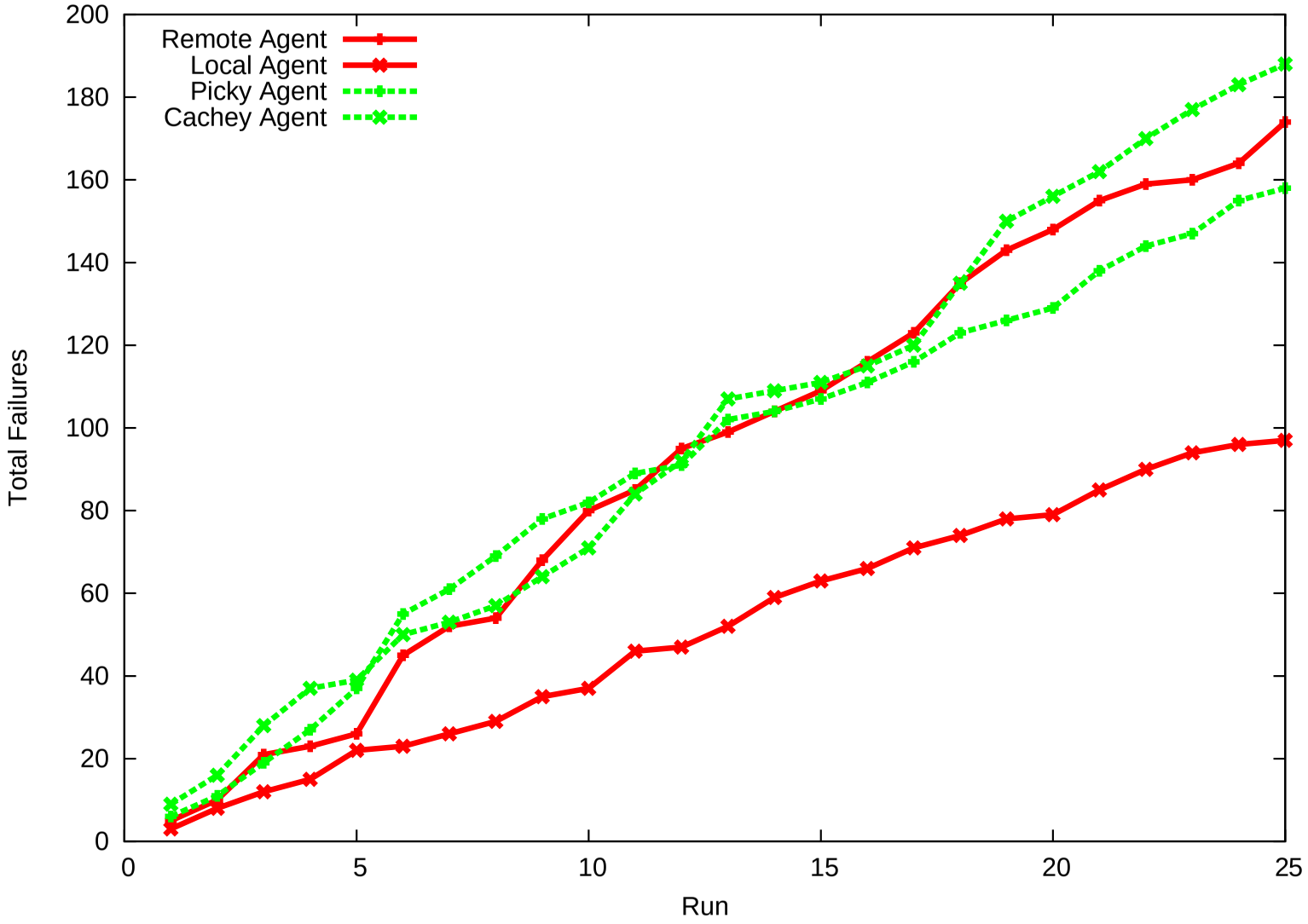


Figure 4.9: Agent failures with no self-tuning.

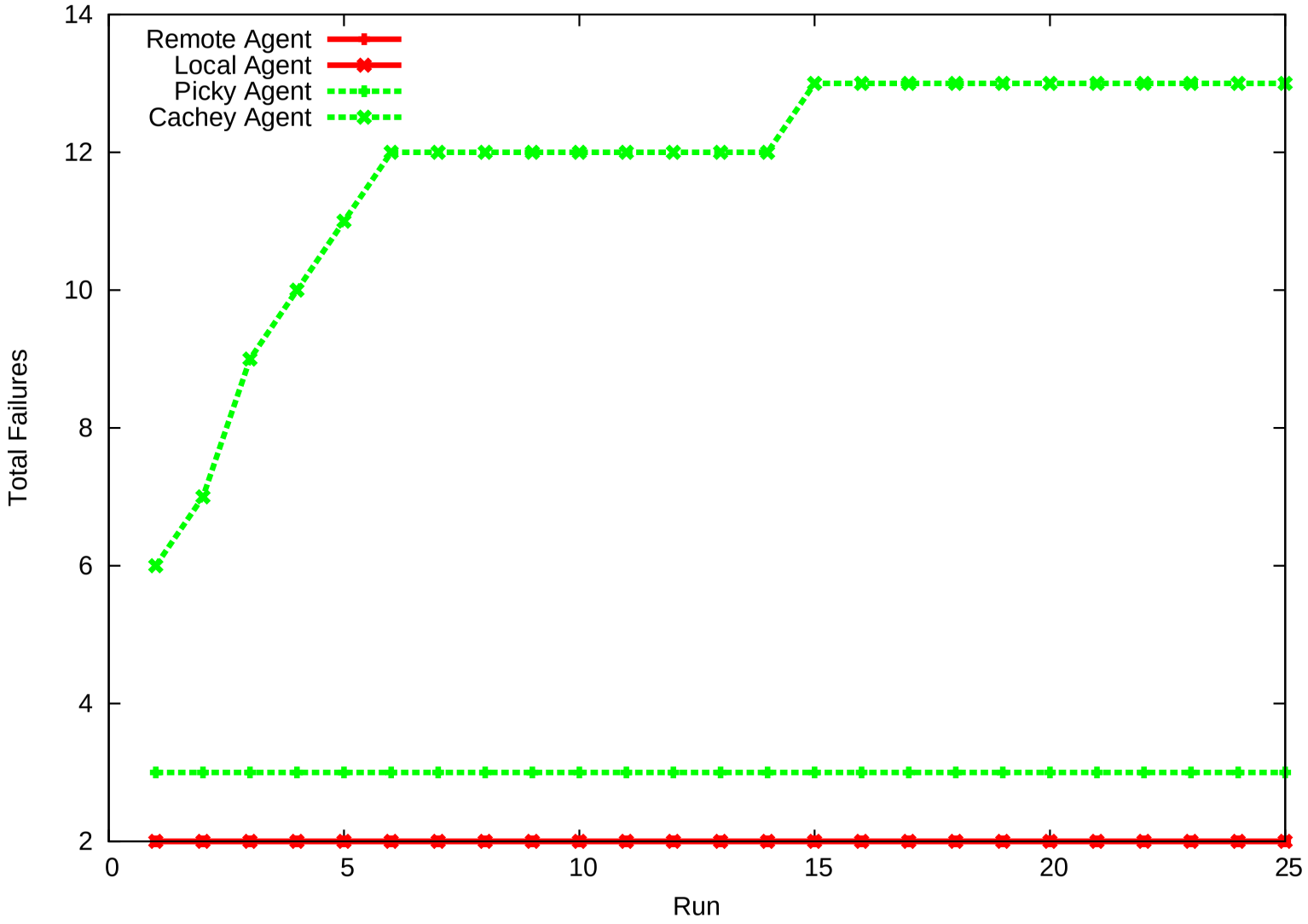


Figure 4.10: Agent failures using action and substate learning for self-tuning.

locating and defusing IEDs. The system divides an area to monitor up among available agents. If the agents detect a suspicious object, they then try to identify the object. Objects determined to be IEDs are then defused by agents with the appropriate capabilities.

The IED detection system we used [58] consists of agents to *Patrol* an area, *Identify* IEDs, and *Defuse* IEDs. The complete role model is given in Figure 4.12. Various agents are capable of playing these roles. The *Patrol* role may be played by our *LargePatroller* or our *SmallPatroller* agents. The *Defuser* role may be played by our *LargeGripper* or *SmallGripper* agents. IEDs may be found while an agent is playing the *Patrol* role, this event will trigger an Identify goal, which in turn could trigger a Defuse goal. The Defuse goal is parametrized on the type of IED identified (large or small). The IED patrol area is first broken into four parts as shown in Figure 4.13.

For the first experiment, we made the *ShortPatroller* fail on area D with a 40% probability for the first 10 assignments made to it. After the first 10 assignments to it, the *ShortPatroller* fails with a 40% probability on area A and no longer fails on area D. The *LargePatroller* agent always fails on area B with a 20% probability. The *SmallGripper* fails with a 100% probability on diffusing large IEDs.

Without learning, in the first 1000 runs, the *SmallGripper* failed a total of 14879 times, the *ShortPatroller* failed 409 times, and the *LargePatroller* failed 107 times. With learning enabled, for the first 1000 runs, the *SmallGripper* failed 1 time, the *ShortPatroller* failed 4 times, and the *LargePatroller* failed 1 time. Subsequent runs using the accumulated knowledge displayed no failures by any agents. This is shown in the bar chart in Figure 4.14. Note the log scale, the failures by the learning system are shown in the bottom area, while the total failures without learning are shown on the top.

In the second experiment, we left the agents the same except for the *LargePatroller*. The *LargePatroller* agent was modified to fail on area D with a 20% probability. This overlaps with the failure area of the *SmallGripper* agent.

In this scenario, without learning, in the first 1000 runs the *SmallGripper* failed 15172

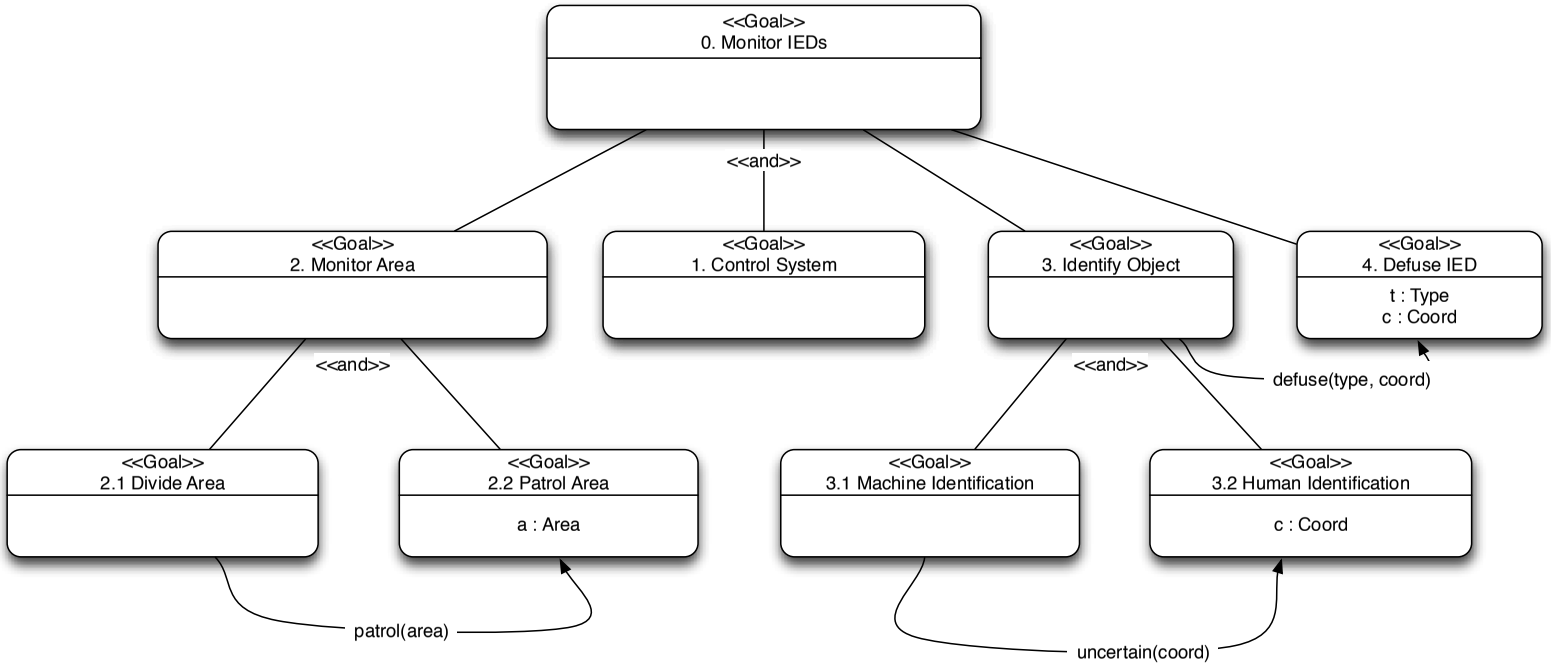


Figure 4.11: Goal Model for IED Detection System.

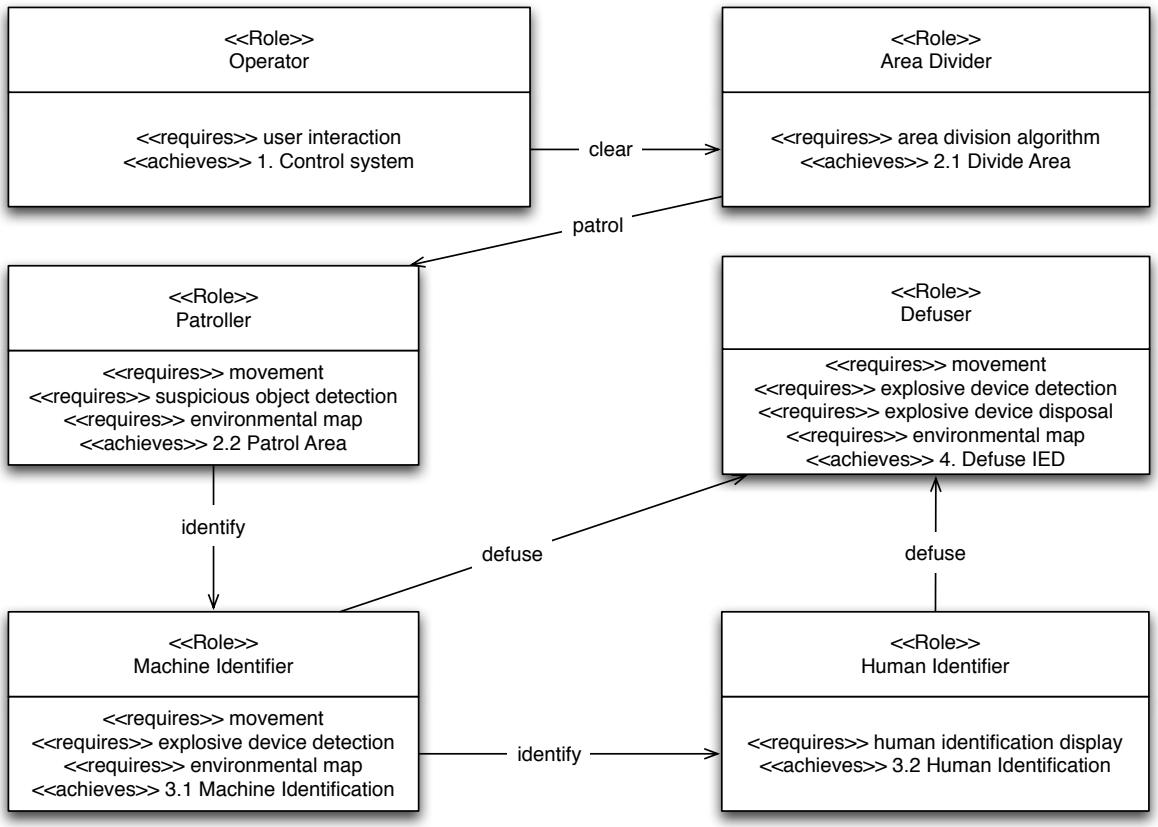


Figure 4.12: Role Model for IED Detection System.

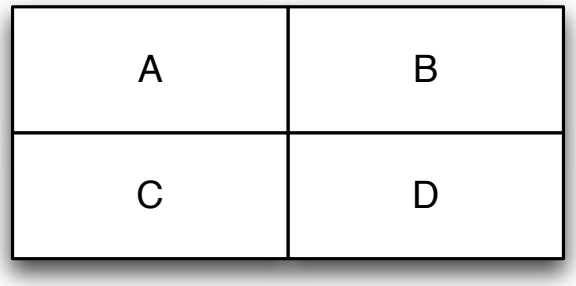


Figure 4.13: IED Search Area for various Patrollers.

times, the *ShortPatroller* failed 434 times, and the *LargePatroller* failed 133 times. With learning enabled, for the first 1000 runs, the *SmallGripper* failed 1 time, the *ShortPatroller* failed 3 times, and the *LargePatroller* failed 12 times. Figure 4.15 gives a bar chart with the results. This chart is again on a log scale.

In a subsequent 1000 runs, using the accumulated knowledge, the learning fell into a sub-optimum, the *SmallGripper* failed 0 times, but the *ShortPatroller* failed 2 times, and the *LargePatroller* failed 102 times. We hypothesize that this is due to the fact that we have the overlapping failing area (*SmallGripper* and *LargePatroller* in area *D*), as well as no partial ordering on learned guidance policies. Thus when the policies must be suspended due to conflicts, or because the system cannot progress with the policies, all the learned policies are suspended at once, creating the situation similar to having no learning. While this would be an interesting avenue of future research, it is outside the scope of this thesis.

4.3.4 Common Results

In all of our experiments, our self-tuning mechanism was able to quickly avoid multiple failure states that had multiple independent sources. The performance of the systems increased as each system was tuned to its environment. The number of polices discovered was kept small, which can be important when considering policies at run-time, since more policies can mean more processing time and effort.

In all of the scenarios, we had multiple independent failure vectors. The learning was

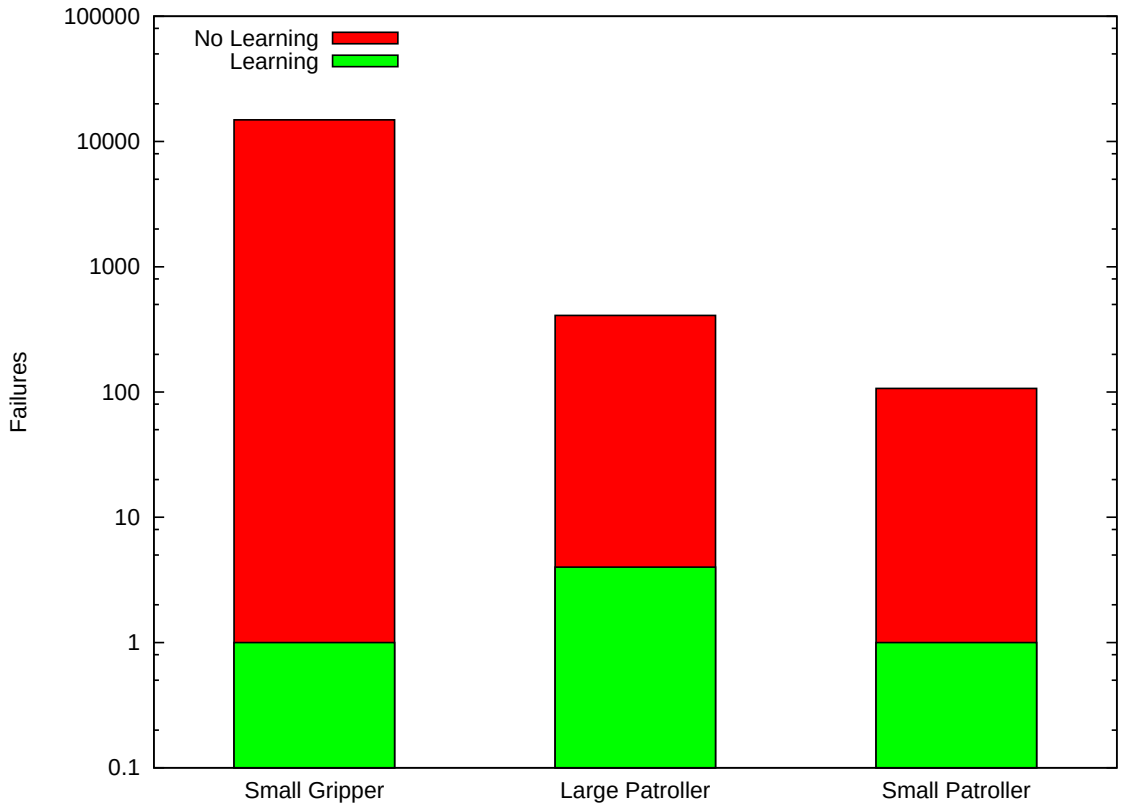


Figure 4.14: IED Scenario 1 Learning Results (log scale).

able to overcome this. The IED simulation explored an evolving failure situation where the cause of the failure changed over time. The information system also had a unique type of failure with the *CacheyAgent*. This agent cached results of previous queries and thus would always succeed once it had successfully retrieved a particular piece of information, otherwise it had a certain probability of failure. This failure was handled by the algorithm, but due to the nature of the policies generated, it was not handled optimally and in a general sense.

4.4 Limitations

As discussed in Chapter 3, guidance policies may be ordered using a *more-important-than* relation. In this work, we did not utilize that ordering. However, we hypothesize that if we ordered the learned policies by confidence, the system would be able to recover from

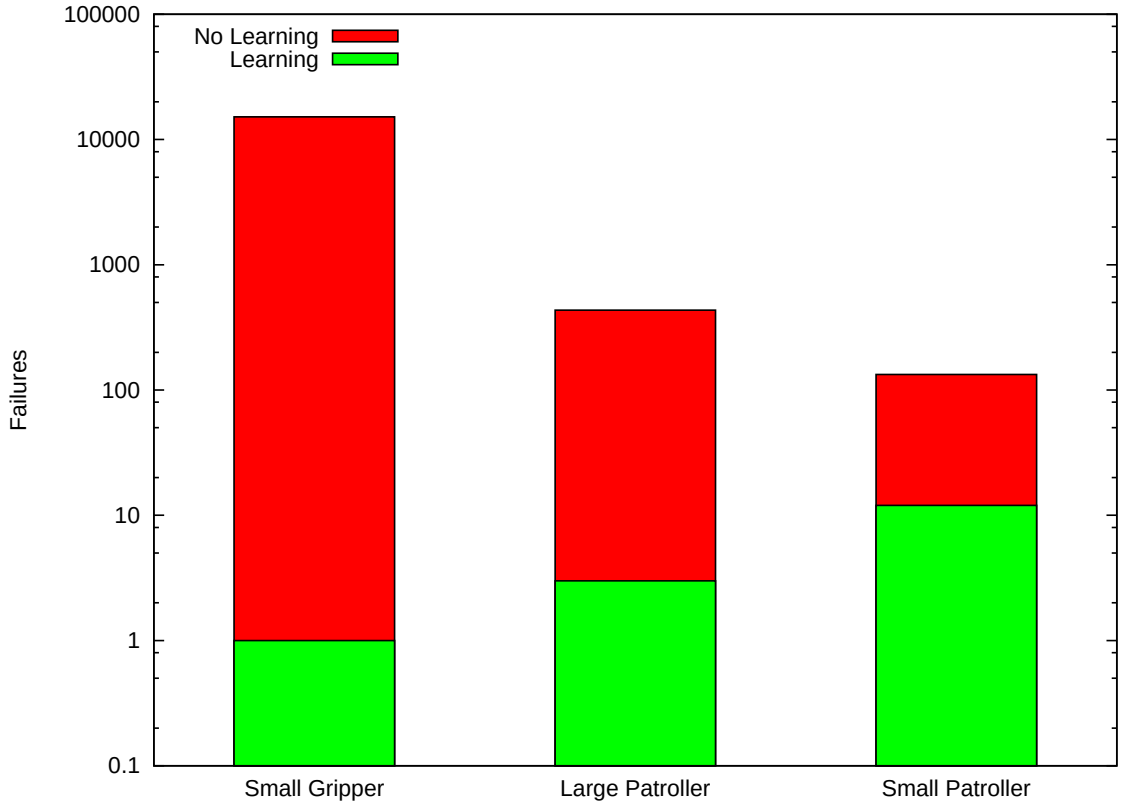


Figure 4.15: IED Scenario 2 Learning Results (log scale).

learning errors more quickly. This is because the learning error policy would have a lower confidence than the other policies and thus would be suspended first in the case of a policy conflict or when the system cannot progress with the current policy set. Confidence may be computed using the score function described in Section 4.2.

Currently the algorithm assumes that only one action happens at a time. The actions of a multiagent system are not always easily serializable. In order to handle concurrent actions, we propose to consider the concurrent actions as a new compound action. In this way you may use this algorithm with minimum modification.

4.5 Related Work

There has been much work in independent agent learning outside of the organizational framework. Much of this learning is on the individual agent level, with the hope that the over-all system performance will improve.

Bulka et al. [59] devised a method allowing agents to learn team formation policies for individual agents using a Q-Learning and classifier approach. They showed notable improvement in the performance of their system. While their approach works well for open multiagent systems, it does not leverage the properties of an organization-based multiagent approach. Abdallah and Lesser [60] developed a similar method to Bulka's except they were concerned with migrating the learned information to a changed network topology as well as using the learned information to optimize the network topology of the current agent system.

Kok and Vlassis [61] used coordination graphs along with a Q-Learning approach to learn to maximize overall agent coordination performance. Again, this work does not leverage the organizational approach to multiagent systems. Every agent is equal in society and only varies with respect to capabilities possessed. In human organizations, structures are built in which actors have roles that they can fill.

Other work has been done at the agent behavior level (e.g. [62]). As an agent tries to achieve a goal, it may affect the performance of its teammates. Policies are sometimes used to restrict the agents behavior while working on a goal.

Chiang et al. [63] have done some work on automatic learning of policies for mobile ad hoc networks. Their learning, however, was an offline approach using simulation to generate specific policies from general 'objectives' and possible configurations. Our research leverages the organizational framework to generate policies online that affect the system through the processes of the organization (i.e role-goal assignments).

4.6 Conclusions

Multiagent systems can become quite complex and may be deployed in environments not anticipated by the system designer. Furthermore, the system designer may not have the resources to spend on hand-tuning the system for a particular deployment. With these issues in mind, we have developed a method to create self-tuning multiagent systems using guidance policies.

Using a variation of Q-Learning, we have developed an algorithm that allows the system to discover policies that will help maximize its performance over time and in varying environments. The use of guidance policies helps remove some of the traditional problems with using machine learning at the organization level in multiagent systems. If the learner creates bad policies, they should not prevent the system from achieving its goal (although they may degrade the quality or timeliness of the achievement). In this way, our approach is 'safer' and thus we can use a simpler learner.

In the experiments we conducted, the system was able to adapt to multiple agent goal achievement failures. It was able to cope with randomized and history-sensitive failures. The learner was able to discover guidance policies which, in every case, caused our systems to perform better on the order of a magnitude when faced with these failures.

Since we are taking the approach of always trying to avoid bad states, there is the question of whether our approach will possibly drive the system away from the optimal state in certain diabolical cases. The argument is that in order to get to the best state, we must pass through some bad states. To address this, we need to look at what is being considered as a bad state and if it is possible for there to be a high-scored state that can only be reached through a bad state. In the experiments we have performed, bad states corresponded to agent goal achievement failures. Using agent goal achievement failures as the scoring method of our states, it is possible that you must pass through a bad state in order to get to an end state with the highest score. But, since the score is inversely proportional to agent goal failures, we will have to go through a bad state in any case. We

argue that since our score is monotonic, our algorithm should be able to drive toward the best scored state even in the diabolical case when you must go through a bad state. This would require that we order our learned guidance policies using the more-important-than relation.

The usage of guidance policies allow for retention of useful preferences and automatic reaction to changes in the environment. For example, there could be an agent that is very unreliable, thus the system may learn a policy to not make assignments to that agent, however, the system may have no alternatives and thus must use this agent. "We don't like it, but we deal with the reality."–that is until another agent that can do the job joins the system.

While we have shown significant improvement using learning to self-tune a multiagent system during runtime, there are advantages to tuning as much as possible during design time. During runtime, some aspects of the system are hard, if not impossible to change. We would also like to drive the design of our system to be as close as possible to the goals of our system—both the hard-goals as well as the soft-goals. In the next chapter, we demonstrate a formal method of generating and analyzing guidance policies for the design of our multiagent systems.

Chapter 5

Abstract Quality driven Policy Generation

5.1 Introduction

Now that we have seen an online approach to automated policy generation in Chapter 4, let us look at an offline approach. Offline approaches have their advantages in that they can be applied in a controlled environment and tested before deployment. A system designer usually has more resources available during development than when the system is deployed. Also, there are changes you can make at design time that are difficult, if not impossible to make during runtime.

In organization-based multiagent systems engineering, the system designer is faced with the task of designing a system to not only meet functional requirements, but also non-functional requirements. System designers need tools to help them generate specifications and evaluate design decisions early in the design process. Conflicts within non-functional requirements should be uncovered and, if necessary, the stakeholders should be consulted to help resolve those conflicts. The approach we are taking is to first generate a set of system traces using the models constructed at design time. Second, we analyze these system traces, using additional information provided by the system designer. Third, we generate a set of policies that will guide the system toward the abstract qualities desired. And, fourth, we analyze the generated policies for conflicts.

5.1.1 Contributions

The main contributions of this chapter are: (1) a formal method for generating specifications at design time for multiagent systems from abstract qualities, (2) a method of automatically discovering conflicts in abstract qualities given a system design, and (3) a way to analyze these conflicts.

5.1.2 Chapter Outline

The remainder of this chapter is organized as follows. In Section 5.2, we present metrics constructed using the ISO 9126 Software Qualities document. Policy generation using trace analysis and a new algorithm for combining generated policies is given in Section 5.3. A method for conflict discovery within the generated policies is given in Section 5.4. A brief analysis of conflicts is presented in Section 5.5. Section 5.6 presents and analyzes experimental results from the application of our policy generation to a variety of multiagent system examples. We describe related work in Section 5.7. Section 5.8 concludes and presents some current limitations of our work.

5.2 Quality Metrics

ISO 9126 [64] defines a set of qualities for the evaluation of software. This document divides software qualities into six general areas: functionality, reliability, usability, efficiency, maintainability, and portability. These characteristics are broad and may apply in different ways to different types of systems. In our research, we defined a group of metrics that evaluate multiagent system traces in order to illustrate our concepts. Each metric is formally defined and may be measured precisely over the current system design. These metrics have been defined to test our process and have not been thoroughly validated through empirical evaluation.

5.2.1 System Traces

Recall our description of a system trace in Definition 3.3. The set of traces form a tree. We use this structure to determine what choices to make at each decision point in order to maximize (or minimize) some metric. The choice may be what role or what agent to use in order to achieve a goal, or even what goal to pursue (in the case of OR goals). It is important to note that the divergence in the traces may also be due to differences in goal parameters, which are normally beyond the control of the system. Thus, the metrics and policies generated may need to take into account some aspect of the goal parameters.

We used Bogor [35] to generate the system traces using the models defined by the OMACS meta-model. Bogor is an extensible, state of the art model checker. Our customized Bogor uses an extended GMoDS goal model, a role model, and an agent model to generate traces of a multiagent system. We have extended the GMoDS model with a maximum and minimum bounds on the *triggers* relationship in order to bound the exploration of the trace-space in the model checker. The traces consist of a sequence of *agent goal assignment* achievements. Recall an *agent goal assignment*, from Definition 4.6, is defined as a tuple, $\langle G_i(x), R_j, A_k \rangle$. We generate only traces in which the top-level goal is achieved (system success). These traces only contain goal achievements that contribute to the top-level goal achievement.

Using the goal model in Figure 5.1, we can generate traces. If we only consider the traces that result in the satisfaction of the top-level goal and using only the goal model (not the role and agent models), we have two possible goal achievement traces as shown in Figure 5.2. Due to the precedence, and the single *or* goal (with two children), there are only two possible paths through the system to achieve the top-level goal. However, when we include the role and agent models, the number of traces may increase due to more combinations of ways to achieve the top-level goal.

We can also consider the role model when generating system traces. This presents a more accurate picture of the system at runtime. Figure 5.3 gives a simple role model for

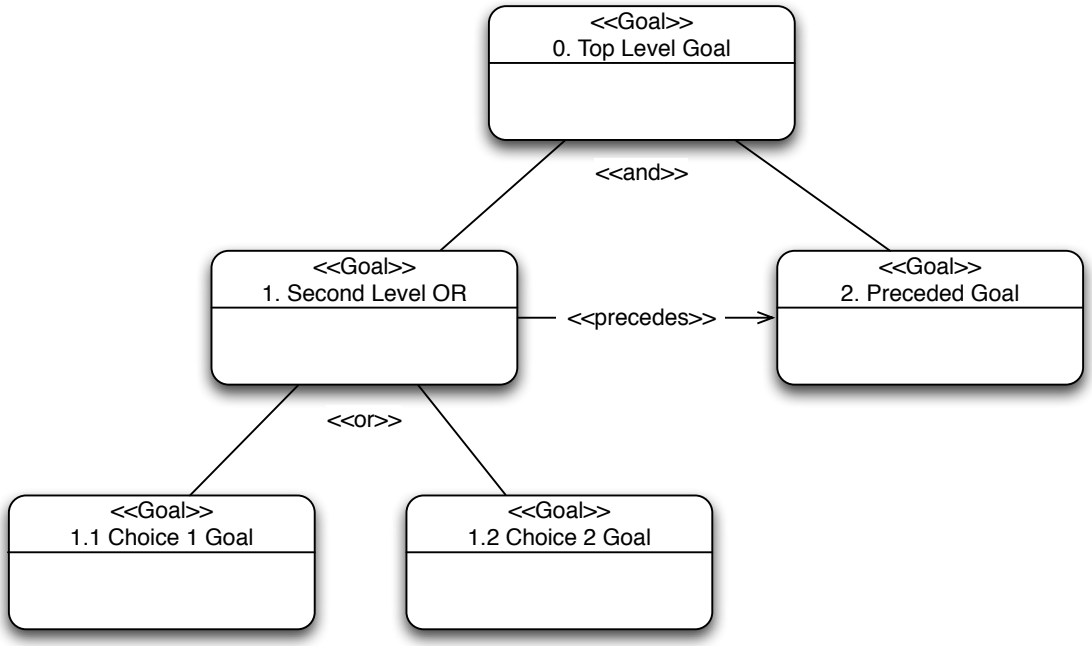


Figure 5.1: Simple example goal model.

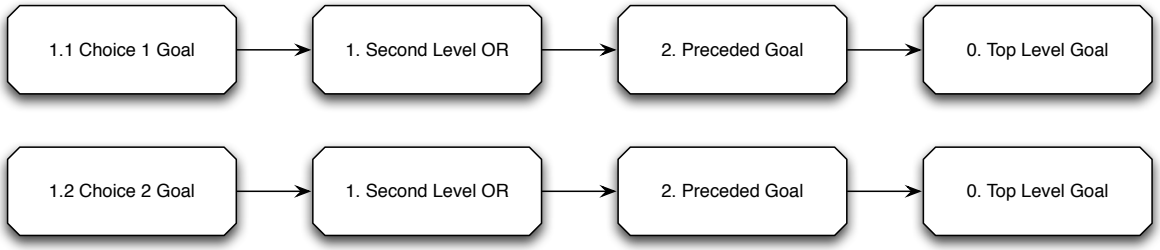


Figure 5.2: Goal only traces.

our goal model. We can quickly see that the role model gives us two ways to achieve the *1.1 Choice 1 Goal*. This choice increases the number of traces. Figure 5.4 depicts the traces when the role model is considered. The shaded trace is the trace that has been added due to the role choice.

The final model we consider when generating traces is the agent model. Figure 5.5 gives a simple agent model for our example system. Including the agent model again increases the number of traces. There are several ways to achieve the top-level goal. Figure 5.6 shows the system traces obtained by using the goal, role, and agent models. The shaded traces

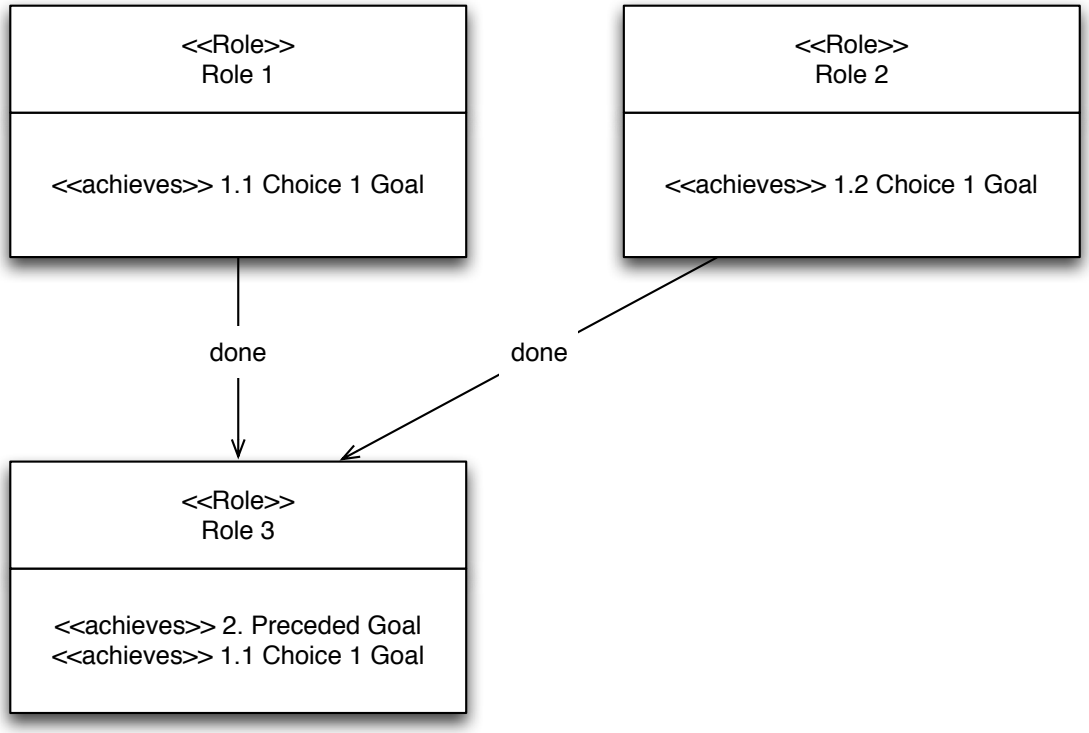


Figure 5.3: Simple example role model.

are the traces added by considering the agent model.

5.2.2 Efficiency

We are using a trace-length based definition of efficiency. The shorter the trace the more efficient is the top-level goal achievement. Our strategy here is to make assignments such that we minimize the total expected trace length. This minimization will be dynamic in that it will take into consideration the current trace progress. Thus we consider goal achievements the system has made when determining shortest trace length to pursue. We then convert this logic statically into a set of policies that when enforced will exhibit the same behavior as a minimization algorithm, given current system goal achievements. Given the initial system state, we prefer to make assignments to achieve the overall shortest path. Thus, we generate directing (guidance) policies that proscribe assignments (although they may

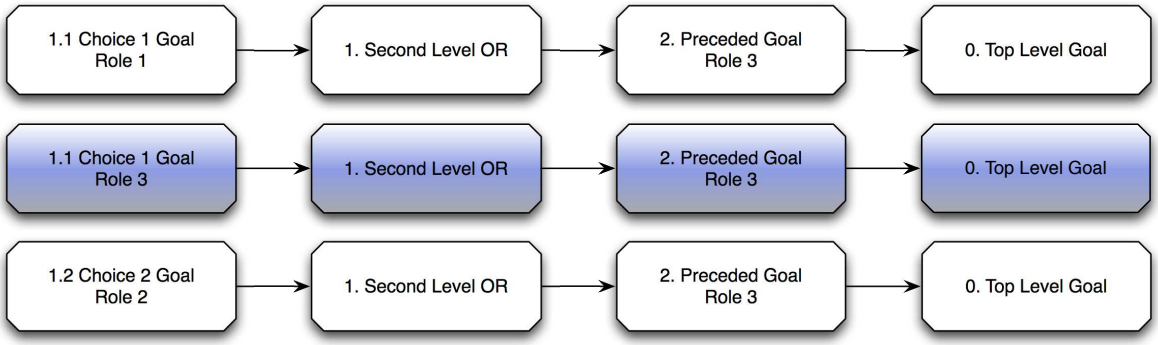


Figure 5.4: Goal-role traces.

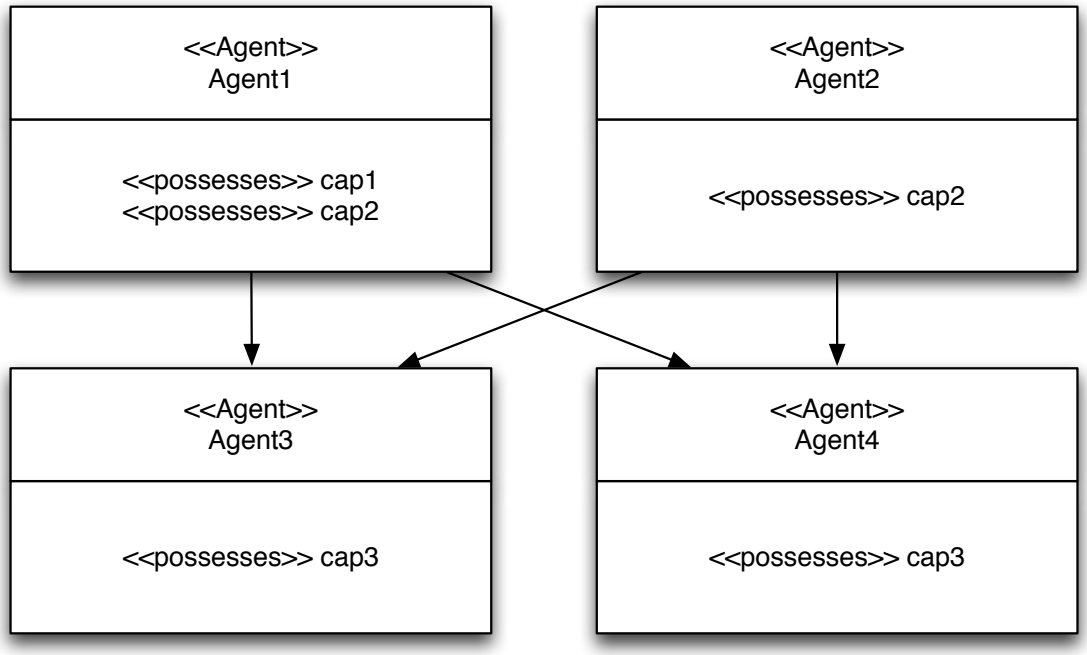


Figure 5.5: Simple example agent model.

present multiple options). Expected trace length is defined in Formula 5.1.

$$\text{ExpLength}(\xi) = \sum_{i=1}^{n} \frac{1}{1 - pf_i} \tag{5.1}$$

ξ represents a single trace, while pf_i is the probability of failure for the assignment achievement i within that trace.

Definition 5.1: Assignment Acheivement. *An* assignment achievement *is the satisfaction of a goal which has been assigned to an agent.*

Figure 5.6: Goal-role-agent traces.

Definition 5.2: Assignment Acheivement Failure. *An* assignment achievement failure *is the failure of an agent to be able to satisfy a goal that has been assigned to it.*

Thus, an *assignment achievement failure* is a failure of the agent to complete its assignment. The probability of failure for the agent goal assignment achievement (pf_i) is the maximum probability of failure for all the capabilities required for the role in the assignment:

$$pf_i = \max_{c_x \in \text{capreq}(As_i)} Pf(c_x, As_i) \tag{5.2}$$

It is evident here that some traces will have an infinite expected length (probability of failure is 100%).

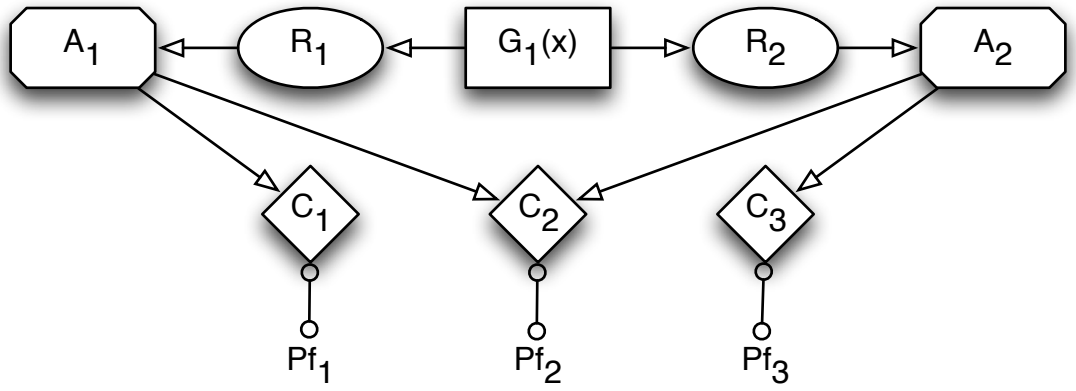


Figure 5.7: Goal Choice & Capability Failure Probabilities

We are focusing on the assignment of goals to agents in the system. A goal assignment choice is depicted in Figure 5.7. $G_1(x)$ represents the parametrized goal that needs to be achieved. R_1 and R_2 are two different roles that are able to achieve the goal G_1. A_1 and A_2 are two agents that posses capabilities required to play R_1 and R_2 respectively. The failure probabilities are connected to each capability.

In our tests, we have used a capability failure probability matrix. This matrix allows us to define the probability of failure for capabilities in various scenarios and will be described in more detail in our evaluation (Section 5.6).

5.2.3 Quality of Product

Quality of achieved goals falls under the ISO software quality of Functionality. Here we define quality as a measure of the quality of goal achievement. Quality of goal achievement may depend on the role, agent, and goal (including parameters). In our analysis, we limit ourselves to these influences although goal achievement quality may depend environment, history of the system, and current assignments.

Definition 5.3: Goal Achievement. *A goal achievement is the satisfaction of a goal that*

has been assigned to an agent. That is, the assigned agent has created the goal's product or reached the goal's achievement state.

Definition 5.4: Quality of Goal Achievement. *Quality of goal achievement is a score given to a goal achievement, such that, if the score of one goal achievement is higher than the score of another achievement for the same goal, the former achievement is said to be of higher quality than the latter.*

Certain roles may obtain a better result when achieving certain goals, likewise certain agents may play certain roles better than other agents. These properties can be known at design time. Usually this intuition is known by the implementers and they may manually design an agent goal assignment algorithm to favor these assignments.

In our analysis and experiments, we mapped assignments to scores. The higher the score, the higher the quality of product. The scores can be specified over the entire assignment, or just portions. For example, role R_1 may achieve goal G_1 better than role R_2 when the parameters of G_1 are of class x. Agents who produce higher quality products could also be part of the score determination.

Definition 5.5: Trace Quality Score. *A trace quality score is simply the average quality of goal achievements over a system trace.*

We realize some products may be more important than others, however, we use a average as given in Formula 5.3. Let ξ_i be the ith agent goal assignment in trace ξ of length n.

$$\text{Qual}(\xi) = \sum_{i=1}^{n} \frac{score(\xi_i)}{n} \tag{5.3}$$

5.2.4 Reliability

Sometimes failure should be avoided at all costs, thus, even if there is a probabilistically shorter trace, it could be the case that we choose the longer trace because we want to minimize the chance of any failure. Formally, we want to minimize goal assignment failures.

We do this by minimizing the probability of capability failure. Our strategy here is to pick the minimal failure trace given the current completed goals in the system.

Definition 5.6: Reliability. *A system is said to be more reliable if it exhibits less agent goal achievement failures. Thus, a system trace with less overall agent goal achievement failures is said to be more reliable than one with more agent goal achievement failures.*

We can use the capability failure probability matrix defined for Efficiency. The score we are minimizing is defined as:

$$\text{Fail}(\xi) = \sum_{i=1}^{n} pf_i \tag{5.4}$$

Where pf_i is defined as in the Efficiency metric (the probability of failure of assignment i within trace ξ).

It is important here to see the distinction between Reliability and Efficiency. Efficiency is concerned with minimizing the expected trace length, while Reliability is concerned with minimizing the total number of failures. Thus, if we are pursuing Efficiency, we may choose a path in which there may be some failures, even through there is a path with no failures, because the expected trace length is shorter in the path with failures. Reliability will always choose a path with less expected failures, even if the path is longer than another.

5.3 Policy Generation

To construct our policies, we first generate a set of traces using our OMACS models as input to our customized Bogor model checker. We then run a metric over each trace, giving it a score. The aim here is to create policies to guide the system to select the highest (or lowest) scoring trace, given any trace prefix. Thus, we create a set of assignments that will guide the system toward the maximum scoring traces. There may be many traces with the same maximum score, in this case we have a set of options. This selection is illustrated in Figure 5.8. We generate policies that, when followed, guide the system to traces that look like the highest scoring traces. Thus, for the figure, we proscribe that from state S_1, you

must make goal agent assignments that are in the highest scoring traces (S_2, S_2', etc). For every subtrace, we generate a set of agent goal assignment options. This may lead to many policies, for this reason, after we generate the initial set of policies, we prune and generalize them. Policies will be of the form:

$$[\text{guard}] \rightarrow \alpha_1 \vee \alpha_2 \vee \ldots \tag{5.5}$$

where α_i is a generalized agent goal assignment and [guard] is a conditional on the state of the system. The guard is also specified in terms of the achieved agent goal assignments.

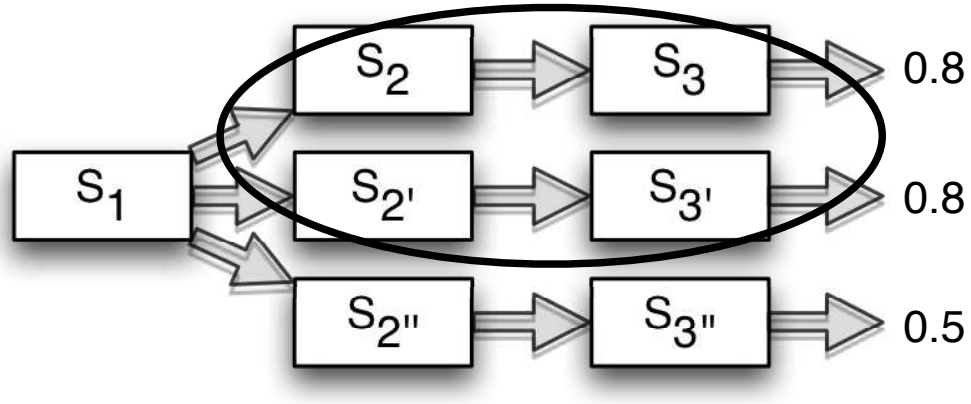


Figure 5.8: System Traces to Prefer

We use two methods to reduce the size of the policy sets generated. One method is to prune useless policies. Since we produce a policy for every prefix trace, we may end up proscribing actions when the system did not initially even have a choice in the matter (the system was already forced to take that choice). We find these policies by checking the traces matched by the policies' left-hand side (the guard). If a policy only matches one trace, we can prune that policy as it had no effect on the system. The policy had no effect because it applied to only one trace. This means that the system had no choice at this point, thus, there is no need to guide the system in a particular way.

Definition 5.7: Prefix Trace. *A prefix trace is any prefix subsequence of a system trace. Thus, if a system trace is a sequence of events, then a prefix trace is any subsequence that includes the initial event.*

The second method combines multiple policies through generalization. If two or more policies offer the same choices for assignments (meaning their right hand sides are the same), the common pieces of the left hand side are computed. If the new left hand construct (the common pieces of the two policies) matches a non-empty intersection of traces with the current policies and the right-hand side of the new policy is not a subset of the right-hand side of each of the matching policies, the potential policy is discarded. Otherwise we remove the two policies that we have combined and add the new combined policy. We repeat this procedure until we cannot combine any more policies. This procedure is described more precisely in Figure 5.9. We repeat this procedure until we do not combine any more policies.

for all $policy$ in $policies$ **do**
  $combine = \emptyset$
  for all $policy2$ in $policies$ **do**
    if $policy \neq policy2 \wedge policy.actions = policy2.actions$ **then**
      $combine = combine \cup policy2$
    end if
  end for
  if $combine \neq \emptyset$ **then**
    for all $policy3$ in $combine$ **do**
      $commonGuard = policy.guard \cap policy3.guard$
      $fail = false$
      for all $policyOld$ in $policies$ **do**
        if $policyOld.guard \subseteq commonGuard \wedge policyOld.actions \not\subseteq policy3.actions$ **then**
          $fail = true$
        end if
      end for
      if $\neg fail$ **then**
        $policies = policies - \{policy, policy3\}$
        $policies = policies \cup \{\langle commonGuard, policy.actions\rangle\}$
      end if
    end for
  end if
end for

Figure 5.9: Policy combining algorithm

5.4 Conflict Discovery

Now that we are automatically generating policies for different abstract qualities, we may generate conflicting policies. After discovering these conflicts, we may use a partial ordering of policies to overcome them or decide to rework our initial system design.

Recall the policy structure in Formula 5.5, since we have this policy structure and we are generating policies for different qualities, we may have different types of conflicts between policies generated for different qualities. These conflicts may be discovered by examining the guard of each policy and checking if there is an non-empty intersection of traces where both guards are active. If the intersection is non-empty and if the assignment choices are not equal, there is a possibility of conflict. Now, it may be the case that the right hand side of both AND'd together are satisfiable with the OMACS constraints, for instance, that only one agent may play a particular instance goal at once (Formula 5.6).

$$Sat((\alpha_x \vee \alpha_y \vee \alpha_z) \wedge (\alpha_a \vee \alpha_b \vee \alpha_c) \wedge \beta) \tag{5.6}$$

In Formula 5.6, each α represents an assignment, while the β represents OMACS constraints as well as any other system policies. Thus, even though we may be able to satisfy the assignment choices (there is a set of truth assignments that make the α portion true), we may still have a conflict due to other OMACS constraints.

Even if the formula is satisfiable, there may still be a need for partial ordering between the policies. Since there may be agent failure, we want to know what policies to relax first.

We can partition the conflicts into two sets: *definitely conflicts* and *possibly conflicts*. The *definitely conflicts* elements will always conflict given the system design. The *possibly conflicts* will only conflict if the configuration of the system changes, i.e., in the case where there is capability or agent loss. If we have statistics on capability failure, we can even compute a probability of conflict. This probability could help the designer determine if the possibility of conflict is likely enough to spend more resources on overcoming it. Some conflicts may be inherent in the design, due to constraints on agents and capabilities or

because of a sub-optimal configuration. Being able to see these conflicts early in the design process (and especially before implementation) will greatly help as it is much cheaper to change the design earlier rather than later.

Definition 5.8: Definitely Conflicts. *Two policies are said to definitely conflict when, given the system design, they always result in a conflict. That is, there is no way for both formulas to hold at the same time and the guards for both may be true at the same time.*

Definition 5.9: Possibly Conflicts. *Two policies are said to possibly conflict when, given the system design and current set of agents, they do not always result in a conflict. However, if an agent's capabilities fail they can result in a conflict. That is, there is a non-empty intersection of assignment proscriptions, but there is also a non-empty difference between assignment proscriptions and the guards for both may be true at the same time.*

If policies generated from different abstract qualities *definitely conflict*, then this is an indicator to the system designer that with the current constraints (agents, roles, and goals), it is not possible to satisfy all of the stake-holder's abstract requirements. The designer and/or stake holder must modify the models by adding agents, changing goals, or by relaxing or redefining the abstract requirement.

We can choose to resolve the conflicts by specifying which quality we prefer in each conflicting case. The designer may prefer efficiency over quality in certain cases and quality over efficiency in other cases. This choice will be a conscious decision by the designer (perhaps after consulting the stake-holders), and thus, a more engineered approach than the ad-hoc and unclear decisions that might be inadvertently made by implementers.

5.5 Conflict Analysis

Once we generate policies using the design models and the abstract qualities desired, we can analyze any potential conflicts between the abstract qualities by analyzing the conflicts between the generated policies. We could simply take each policy from a set of policies

generated for a particular quality and determine if it conflicts with any policy generated for a different quality. This makes our potential conflict space large and unmanageable. If we are only analyzing conflicts between two qualities, the potential conflict space is $P_1 \times P_2$. Where P_1 and P_2 are the sets of policies generated to support quality Q_1 and Q_2 respectively.

To make the conflict analysis more tractable for the designer, we make an analysis of the parts of the policies that are the point of conflict. These points of conflict tend to be repeated. Thus, by looking at only the points of conflict we are able to summarize the conflict information in a format to allow a system designer to more easily make decisions concerning the conflicts. This analysis will be explored in more detail in the following chapter.

5.6 Evaluation

We took four different multiagent systems to test our policy generation. The Cooperative Robotic Floor Cleaning Company (CRFCC) described in Section 3.2.2. The second system we used is the Improvised Explosive Device (IED) Detection System as described in Section 4.3.3. The third example is the Information System described in Section 4.3.2. The fourth example is the Conference Management System described in Section 3.2.1. In all four systems, we evaluated the policy generation for all three of our metrics.

5.6.1 CRFCC

Augmenting the models in Section 3.2.2 with the collapsed capability failure probability matrix in Figure 5.10, we computed efficiency policies. Capabilities not listed are expected to have a 0 probability of failure.

Capability/Assignment	$*$
mop	0.5
sweep	0.1

Figure 5.10: CRFCC Goal Assignment Choice with Capability Failure Probabilities

We ran Bogor over the models described in Section 3.2.2 (goal, role, and agent), using a limit of five triggers for each triggered goal. The total number of traces generated by Bogor was 56. The maximum probabilistic trace length was 21, while the minimum was 11. The average probabilistic length was 18.9. The total policies generated were 291. Fifty of those policies only matched one trace, and thus, were thrown out. The remaining policies were then transformed by collecting policies whose right hand side were equal and finding common elements on the left hand side. If and only if these common elements were a subset of the left hand side of any other policies and the right hand side was a subset, then this consolidation was allowed. Using this method, we reduced the number of policies to 36. An example policy is given in Figure 5.11.

$$\begin{array}{rcl} < Agent2, Pickuper, Pickuparea() >: 4 & & < Agent2, Pickuper, Pickuparea() > \\ < Agent1, Organizer, Dividearea() >: 1 & => & < Agent5, Vacuummer, VacuumArea() > \\ < Agent5, Vacuummer, VacuumArea() >: 1 & & \end{array}$$

Figure 5.11: CRFCC Generated Policy

The left side of the policy is the guard, in Figure 5.11, each of the agent goal assignments on the left hand side are AND'd together (they must all be true). The number after each agent goal assignment is the minimum number of agent goal assignment achievements that must have occurred thus far to make the assignment clause true. Each agent goal assignment on the right hand side is an option the system may take when choosing agent goal assignments in order to follow a minimum probabilistic trace.

We generated the policies and ran a simulation of the CRFCC system. The average of 1000 runs at each number of rooms was computed. We plotted the total number of assignments the system made to achieve its objective. This allows us to evaluate the impact of the policies.

Figure 5.12 gives the results for a system with the generated efficiency policies and one without the generated policies. The plot clearly shows that the system with the generated

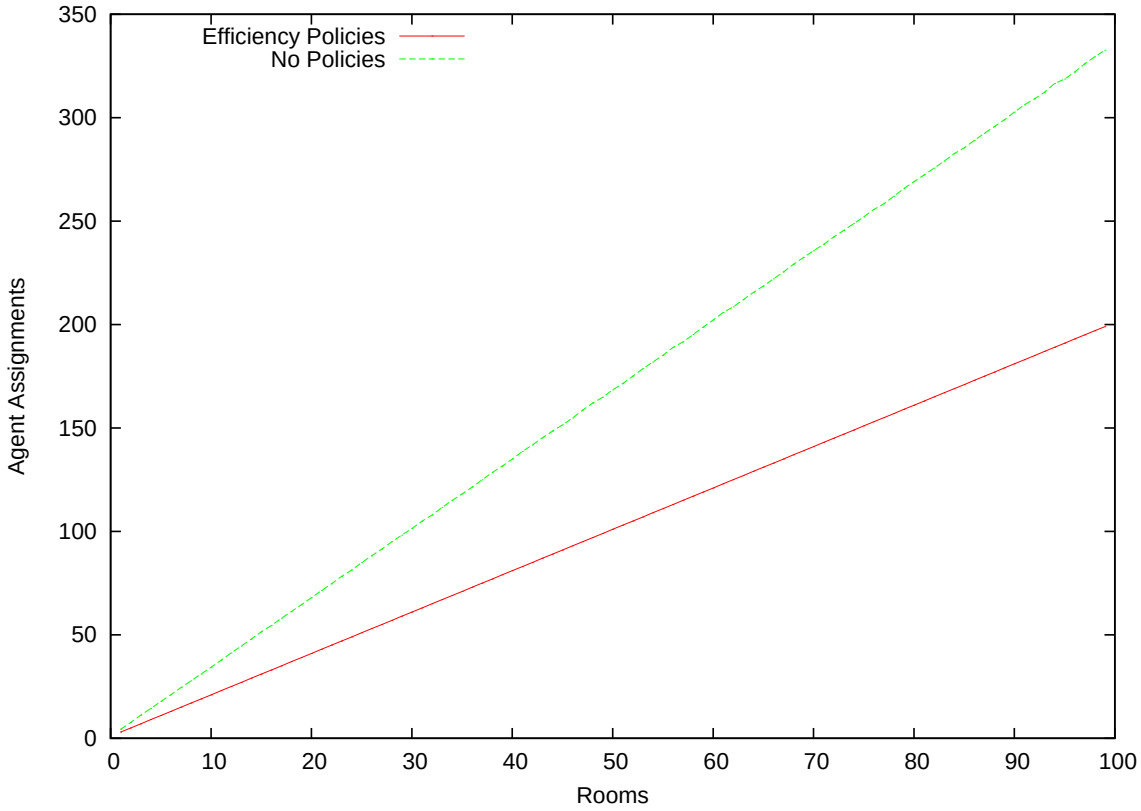


Figure 5.12: Efficiency Policy Generation Effects on Assignments

policies is guided toward efficiency, while the system without the policies has a much lower efficiency.

Likewise, for reliability, we generated reliability policies and ran a simulation of the CRFCC system. The average of 1000 runs at each number of rooms was computed. We plotted the total number of agent achievement failures in the system.

Figure 5.13 gives the results for a system with the generated reliability policies and one without the generated policies. When reliability was the focus, the system was able to keep failures to 0. This was due to the system only assigning to agents who did not fail.

Figure 5.14 gives the results of applying our quality policies to the simulation. In this metric, we used a partial ordering of quality of goal assignment achievements. That is, certain goals, when achieved by certain agents, playing certain roles attain a higher quality of product than some other goal assignment achievement.

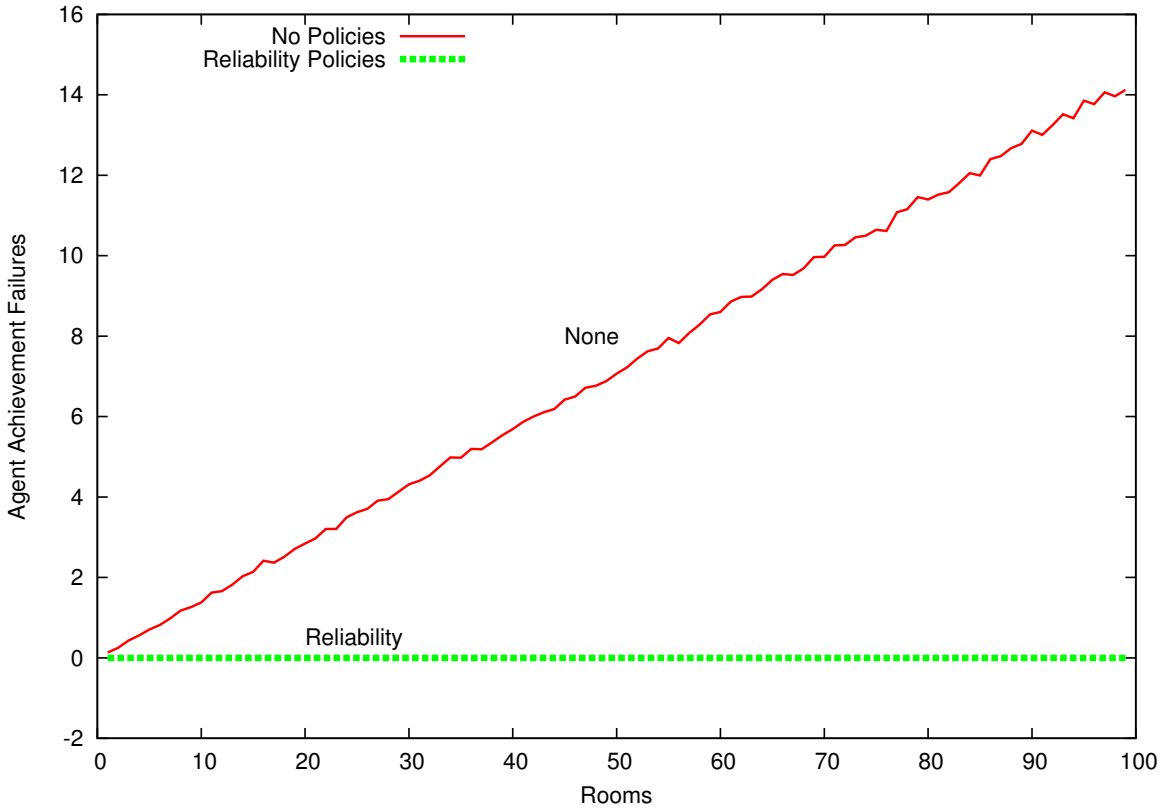


Figure 5.13: Reliability Policy Generation Effects on Assignments

$$\langle Agent^3, Sweeper, Sweep(*)\rangle > \langle Agent^4, Sweeper, Sweep(*)\rangle$$
$$\langle Agent^3, Sweeper, Sweep(*)\rangle > \langle Agent^5, Sweeper, Sweep(*)\rangle \quad (5.7)$$

Formula 5.7 gives the partial order we used for this experiment. Agent 3 quality of product when achieving the Sweep goal using the Sweeper role is better than both Agent 4 and Agent 5.

5.6.2 IED Detection System

We augmented the models in Section 4.3.3 with the collapsed capability failure probability matrix for the IED detection system shown in Figure 5.15. Capabilities not listed have a 0 expected probability of failure. We generated policies by analyzing the traces generated

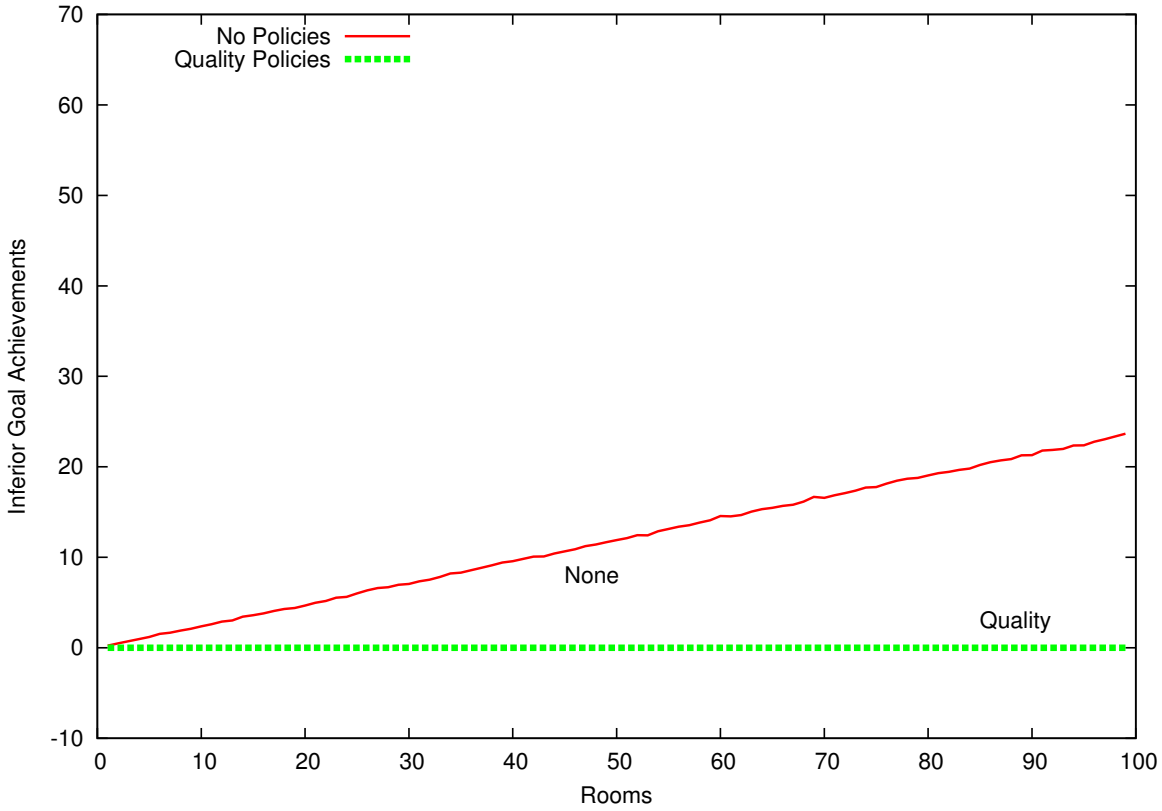


Figure 5.14: Quality Policy Generation Effects on Quality of Goal Achievement

over the models. The system initially generated 209 policies, after automatic pruning and generalization, we had 45 policies. We then ran the system using a simulator, breaking up the search area into pieces from 1 to 99. At each number of search areas, we ran the simulation 1000 times and took the average of the results.

Capability/Assignment	$*$
$movement/SmallPatroller$	0.5
$dispose/SmallGripper$	0.1

Figure 5.15: IED Goal Assignment Choice with Capability Failure Probabilities

The policies forced the system to never have an agent failure. This is reflected in the graph in Figure 5.16. As can be seen, the number of agent assignments with the generated policies is less. This is because in the case of agent failures the goal (task) must be reassigned.

Using the same algorithm to generate efficiency policies, we obtain the results in Fig-

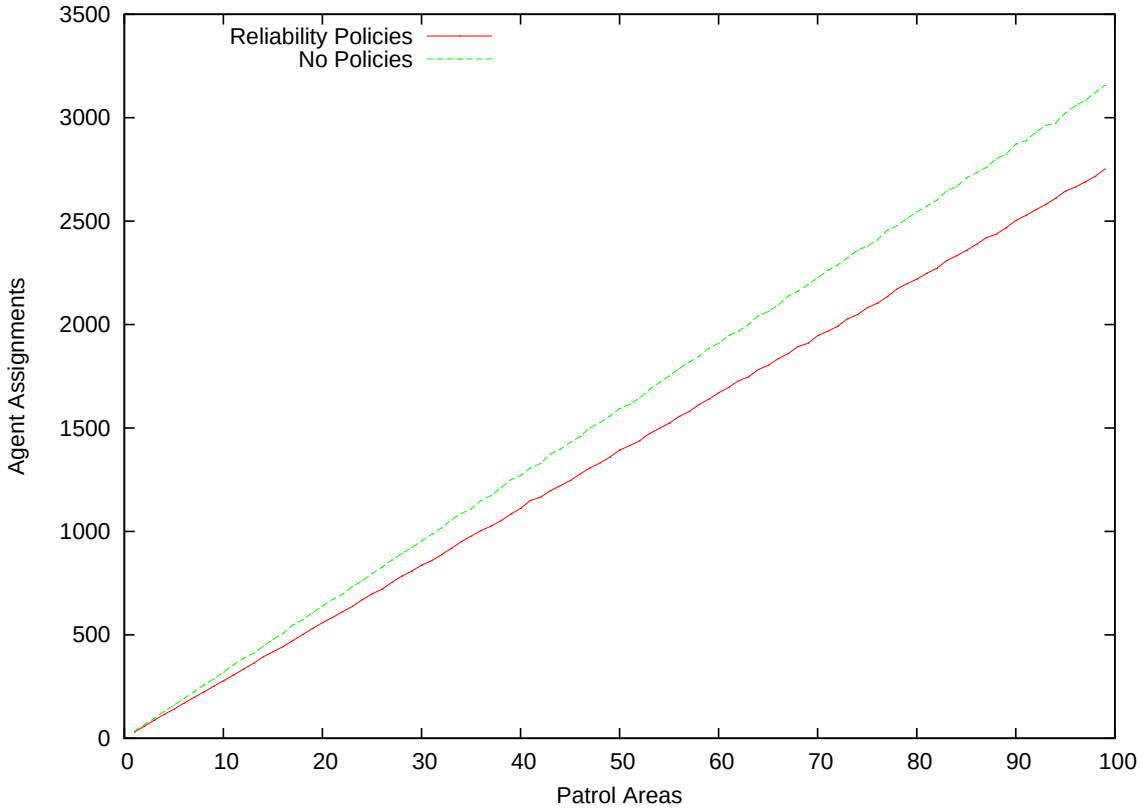


Figure 5.16: Reliability Policy Generation Effects on Assignments

ure 5.17. These results are very similar to the reliability results obtained above. This is due to the reliability and efficiency mapping into the same function for this scenario.

We also generated quality of goal achievement policies. In our quality model, the *LargePatroller* achieved the *PatrolArea* goal with a higher quality than the *SmallPatroller* achieved the same goal. We ran the simulation from 0 to 60 areas to patrol and took the average of a 1000 runs for every set of areas. Without the quality policies in force, the simulation assigned the *SmallPatroller* and *LargePatroller* nearly equally to achieve the *PatrolArea* goal. With the generated quality policies in force, the simulation always assigned the *PatrolArea* goal to the *LargePatroller* thus achieving the highest possible quality of goal achievement.

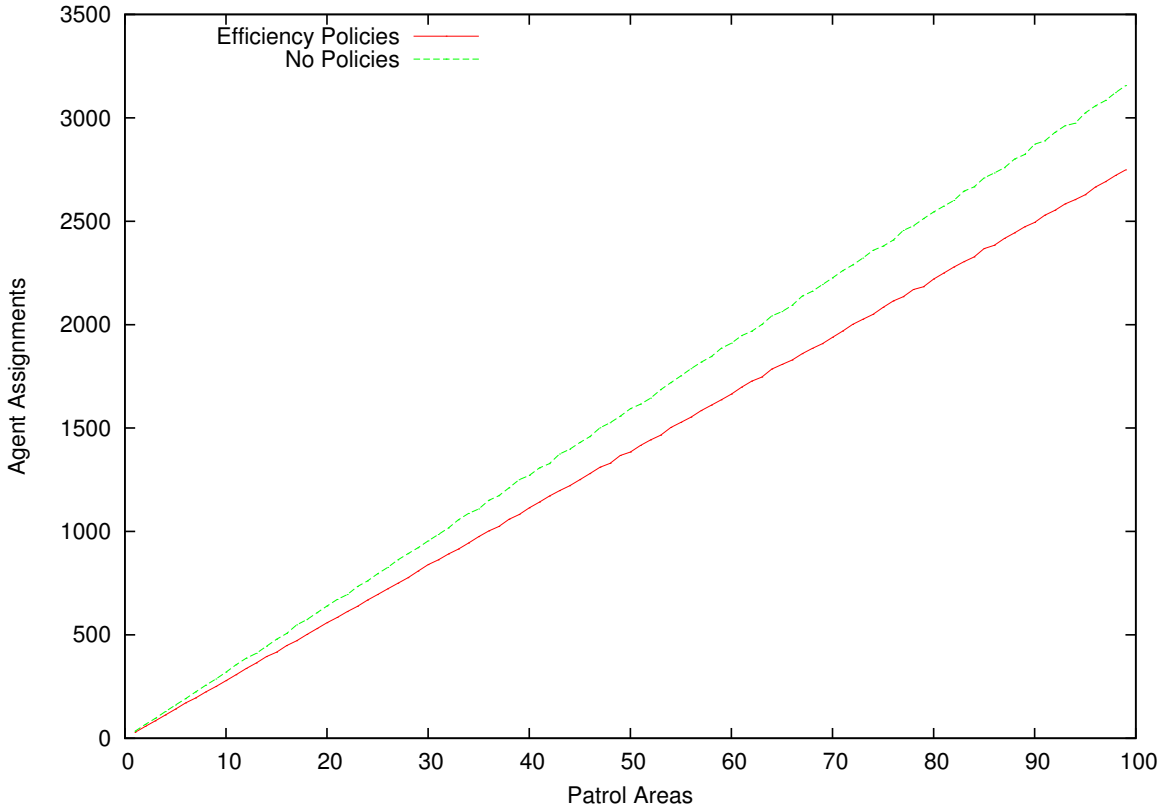


Figure 5.17: Efficiency Policy Generation Effects on Assignments

5.6.3 Information System

Beginning with the Information System described in Section 4.3.2, we introduced further knowledge about failure probabilities. In our information system we had four types of information retrieval agents: *CacheyAgent*, this agent fails with a 30% probability the first time it is asked for a certain piece of information, subsequent requests for info it has retrieved previously always succeeds; *LocalAgent*, this agent fails 100% of the time when asked for remote information, otherwise it succeeds with a 100% probability; *PickyLocalAgent*, this agent fails 100% of the time on any request except for on particular piece of local data; and *RemoteAgent*, this agent fails 100% of the time on all data except for remote data.

We generated a set of *quality* policies using the following properties: the *Remote Retrieval* role achieves a better quality of product than the *Local Retrieval* role for any goal

parameter. However, the *PickyLocalAgent* performs the best when using the *Local Retrieval* role to achieve the *Retrieve Information* goal for any parameter. Using the automatic policy generation we generated 627 policies, which were than reduced to 69 using the techniques described in Section 5.3. We then ran simulations, the results showed that when the policies were enforced, we always achieved the highest quality results, without the sacrifice of any additional failures.

We also generated a set of *efficiency* and a set of *reliability* policies. These policies slightly improved both the efficiency and reliability, but were not able to improve it significantly due to resource limitations. There were simply not enough reliable agents to avoid failure altogether.

5.6.4 Conference Management System

Beginning with the Conference Management System (CMS) example described in 3.2.1, we extended it with additional choices for achieving goals by modifying the goal, role, and agent models.

Cap./Assign.	$\langle *, *, PR \rangle$	$\langle Thr, *, SR \rangle$	$\langle App, *, SR \rangle$
ReviewerInterface	0	0.5	0
Cap./Assign.	$\langle *, Part, NPC \rangle$	$\langle *, Part, RPC \rangle$	$\langle *, Part, BPC \rangle$
PCMemInterface	0.1	0	0.5

Figure 5.18: Capability Failure Probabilities

We augmented our models with a capability failure probability matrix 5.18 and a partial ordering 5.20. In our assignments '$*$' represents the wild card element. Agent type abbreviations are given in Figure 5.19.

Figure 5.18 gives an abbreviated capability failure probability matrix for our system. *ReviewerInterface* and *PCMemInterface* are capabilities defined in the CMS role model. The assignment is represented by a tuple containing parameters, goal, and agent. 'Thr' and 'App' represent theory and application paper parameters respectively, while 'Part' represents

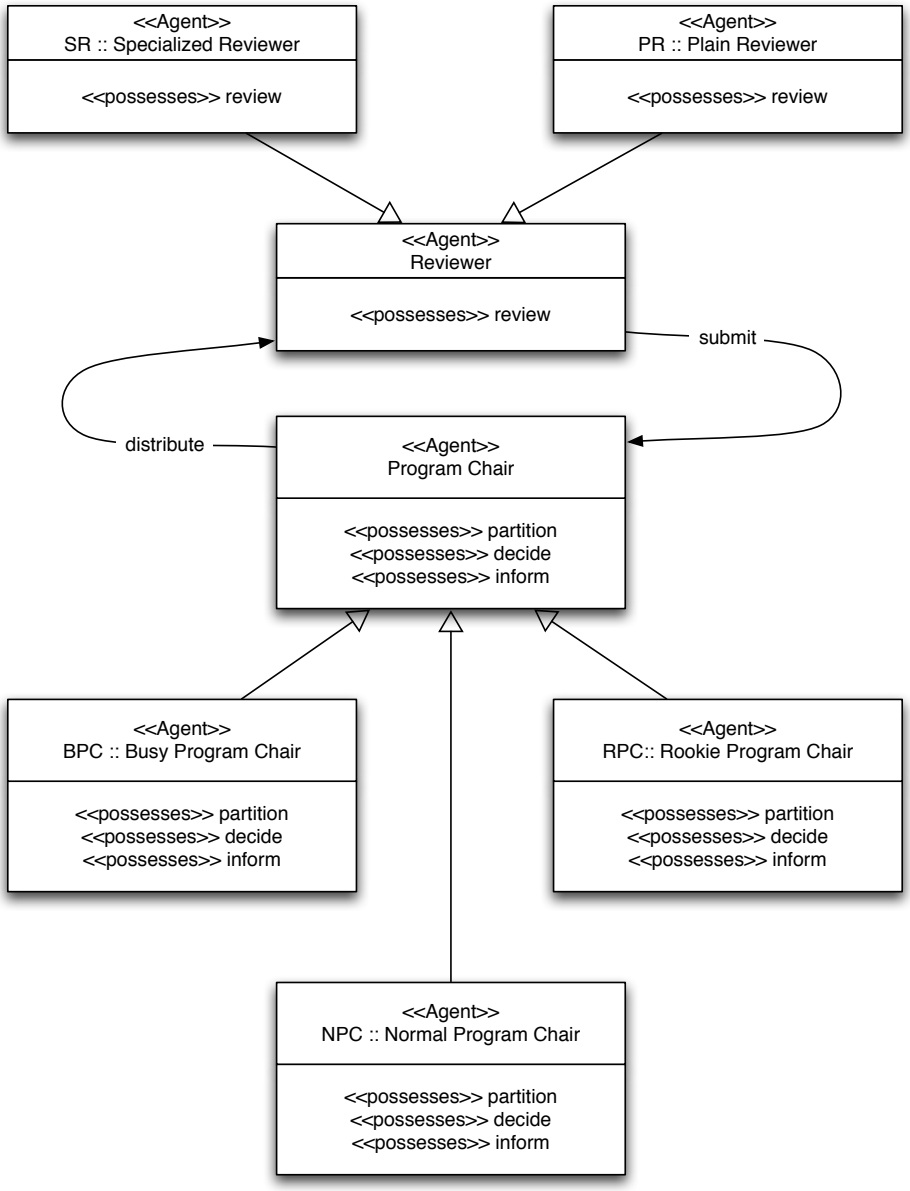
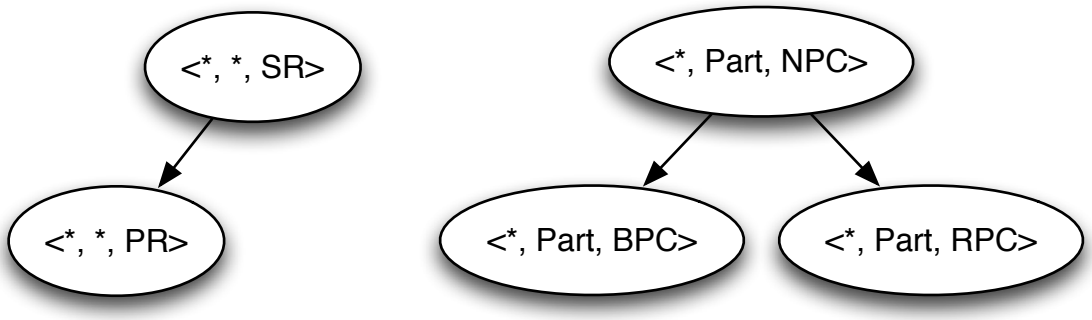


Figure 5.19: CMS Agent Model Augmentation

the *Partition* goal. Thus, the *ReviewerInterface* fails with a 50% probability when being used by the *Specialized Reviewer* on goals parametrized by theory papers. Our quality of product ordering is depicted in Figure 5.20. Nodes represent *agent goal assignments*, while a directed edge from node N_1 to N_2 indicates that the assignment in N_1 produces a higher quality of product than the assignment in N_2.



(a) Review Assignments (b) Partition Assignments

Figure 5.20: Quality of Product Ordering

We ran our customized Bogor on the goal, role, and agent models to generate traces for our system. Bogor produced 2592 unique system traces. Using this information along with our failure matrix and quality orderings, we then produced policies to guide the system toward the abstract qualities desired by the system designer.

We loaded our policies into a simulation engine, which ran the Conference Management System to test the effects of having the generated policies. The simulator picks a random role and agent who is capable of achieving a goal without violating any policies (or, if necessary for progress, violating guidance policies) and achieves an active goal. This is repeated until either the top-level goal is achieved (system success) or we cannot make an more progress (system failure). We varied the number of papers submitted to the system from 1 to 100 and took an average of 1000 runs for each number of papers.

Figure 5.21 shows the results of the policies generated using the efficiency metric on the number of assignments used to achieve the top-level goal. The top line is without policies while the lower line is with the generated policies enabled. The policies are clearly having an effect on the system assignments (and thus efficiency).

To evaluate the impact of our reliability policies, we measure the number of agent assignment failures. That is, we counted the number of times an agent failed to achieve an assigned goal. For the runs using the generated policies, it is not surprising that we did not

have a single agent failure. The runs without employing the policies, however had many agent failures as depicted in Figure 5.22 (note line on the x-axis).

To evaluate the quality policies, we measured how many times the system produced a lower quality result when it could have produced a higher one. Figure 5.23 (note line on the x-axis) shows that without the generated policies, our system produced much lower quality products than with the generated policies.

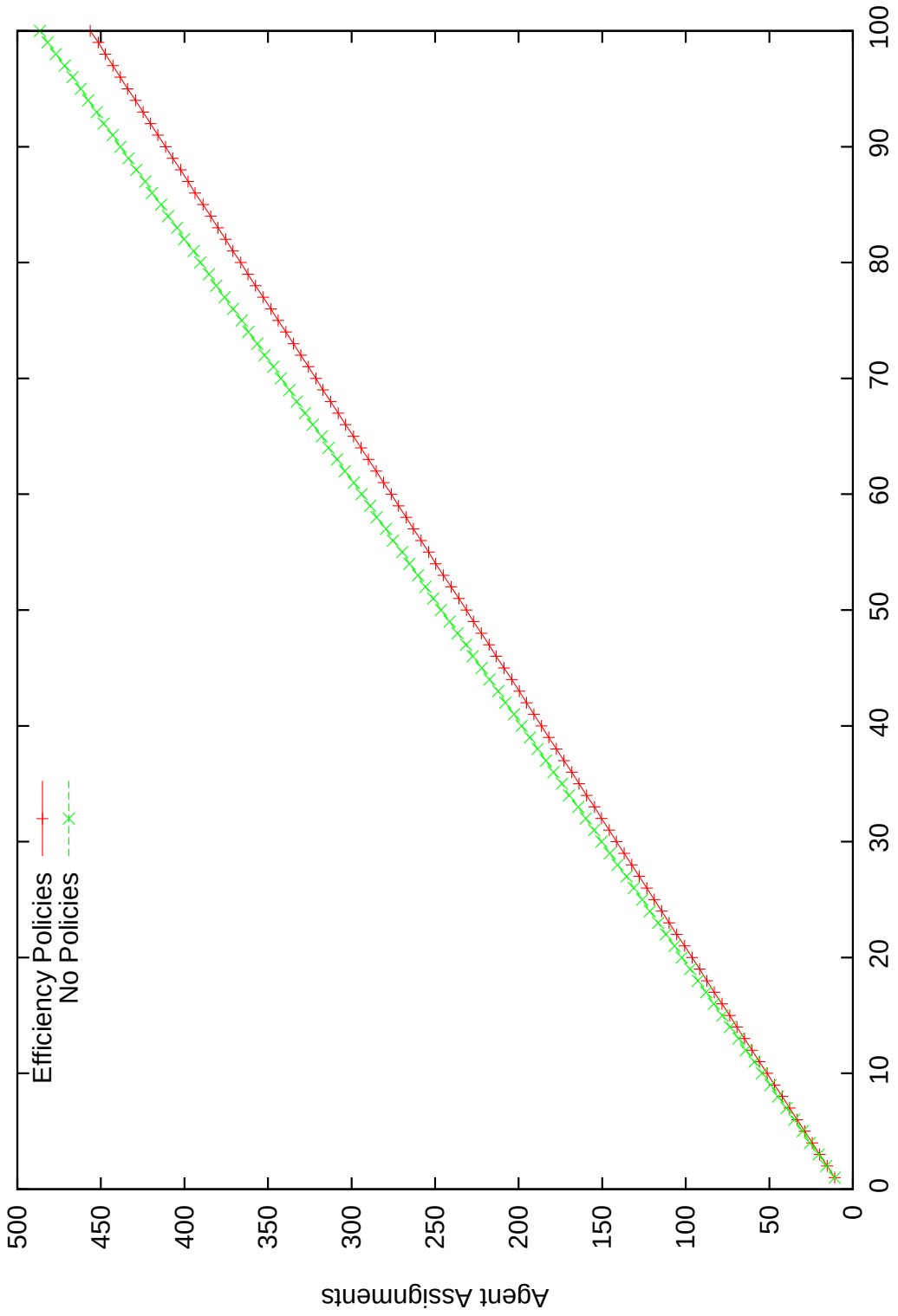


Figure 5.21: CMS Efficiency Results (Lower is Better)

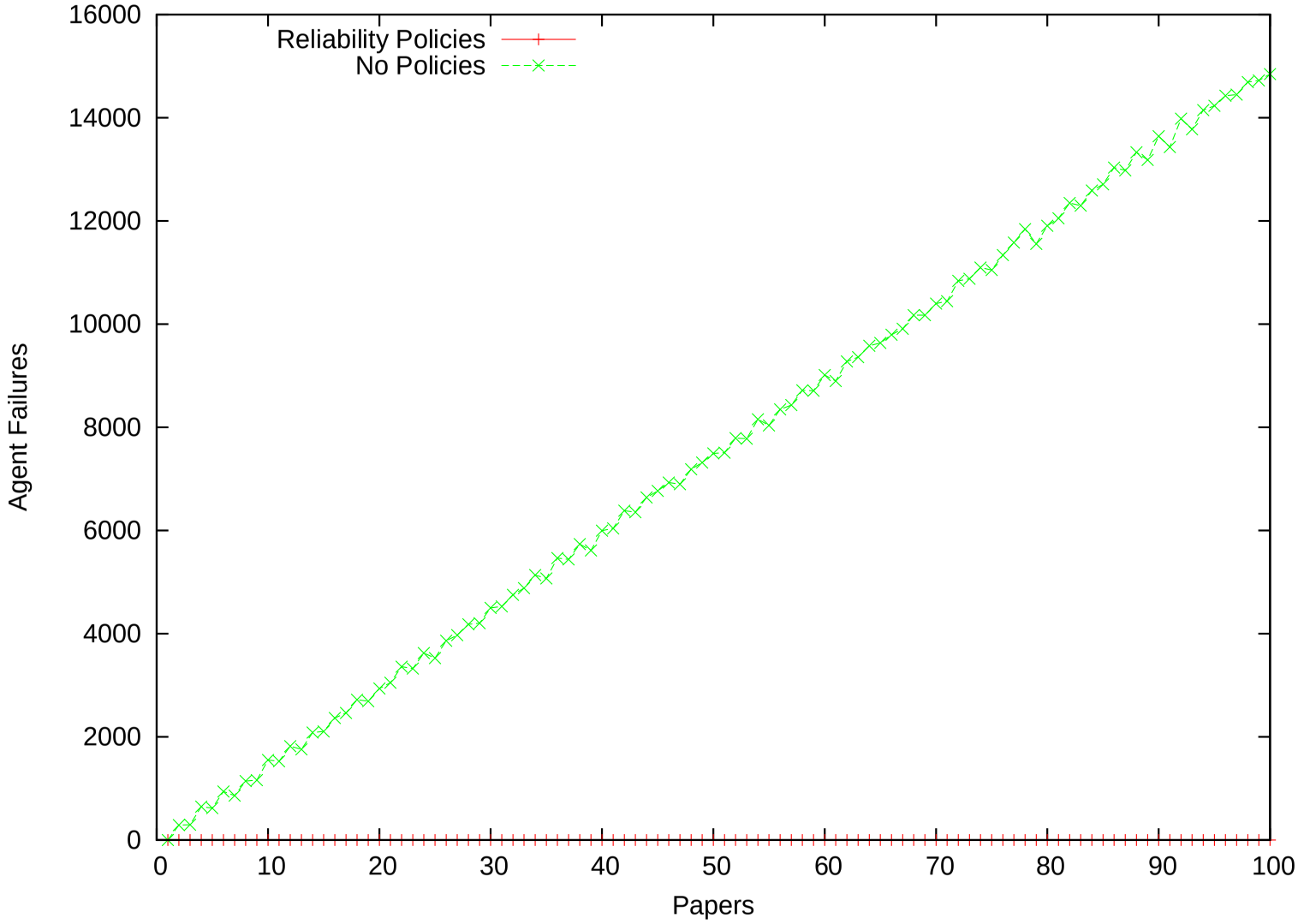


Figure 5.22: CMS Reliability Results (Lower is Better)

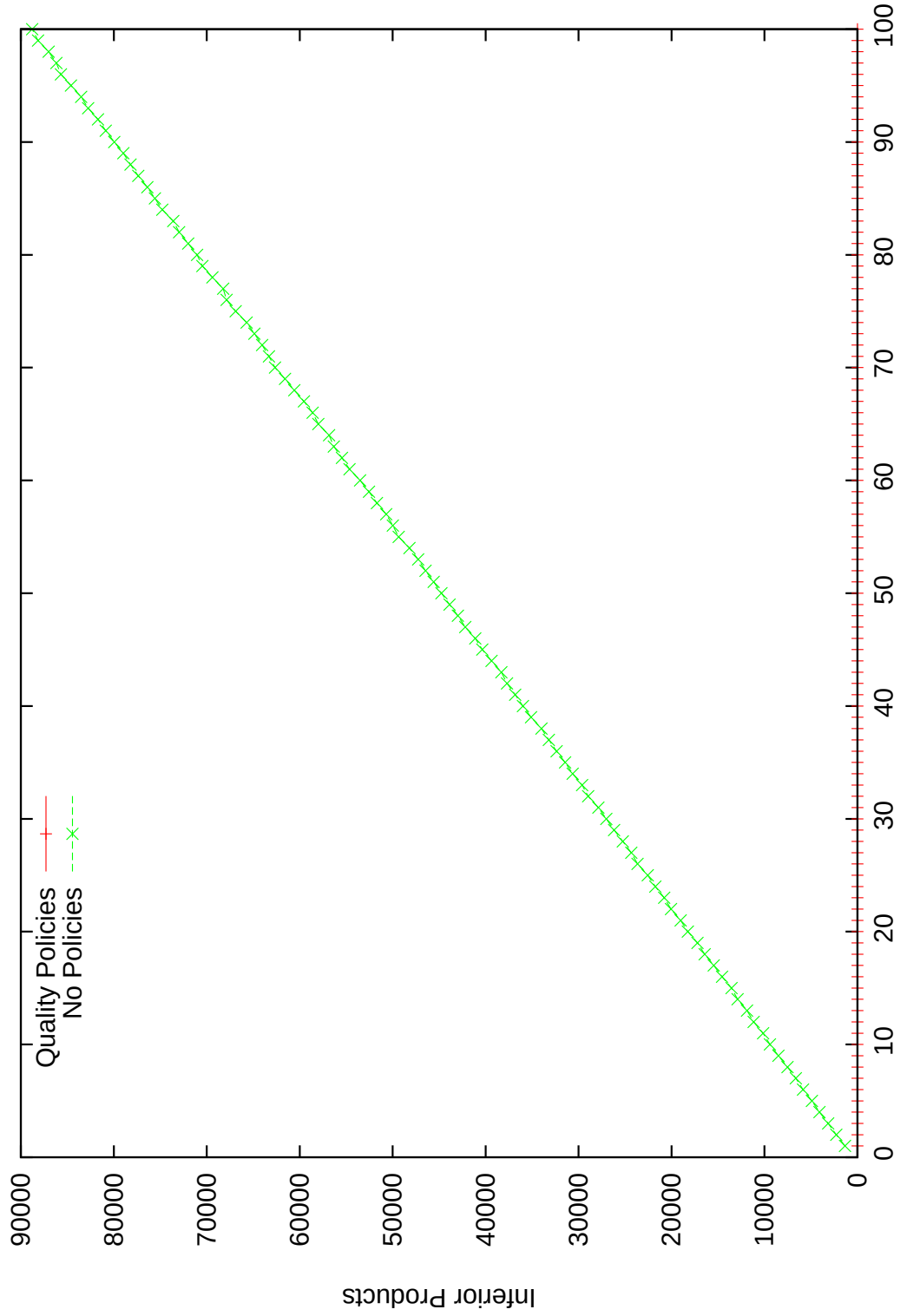


Figure 5.23: CMS Quality Results (Lower is Better)

5.7 Related Work

There has been work in incorporating abstract qualities into multiagent systems. Tropos defines the concept of a soft-goal [19] that describes abstract qualities for the system. These soft-goals, however, are mainly used to track decisions in the goal model design for human consideration.

Some work has been done on model checking multiagent systems [35, 65]. While this work has helped the designer by providing some feedback on their design, it has not yet leveraged model checking to help automate the design process to the degree we present.

Automated policy generation has been researched for online learning [66]. Although these methods help the multiagent system better tune to the environment in which it is deployed, they do not help the designer with the construction of the initial system.

Chiang et al. [63] have done some work on automatic learning of policies for mobile ad hoc networks. Their learning was an offline approach using simulation to generate specific policies from general 'objectives' and possible configurations. This work, however, did not provide the designer with feedback on possible conflicts between 'objectives'.

5.8 Conclusions

We have provided a framework for stating, measuring, and evaluating abstract quality requirements against potential multiagent system designs. We do this by generating policies that can be used either as a formal specification, or dynamically within a given multiagent system to guide the system toward the maximization (or minimization) of the abstract quality constraints. These policies are generated offline, using model checking and automated trace analysis.

Our method allows the system designer to see potential conflicts between abstract qualities that can occur in their system. This allows them to resolve these conflicts early in the system design process. The conflicts can be resolved using an ordering of the qualities that can be parametrized on domain specific information in the goals. They could also cause a

system designer to decide to change their design to better achieve the quality requirements. It is easier to make these changes in the system design than in the implementation.

These policies can be seen to guide the system toward the abstract qualities as defined in the metrics. Our experiments showed significant performance, quality, and reliability increases in our enhanced system over similar systems without the automated policy generation.

Chapter 6

Using Unsatisfiable-Core Analysis to Explore Soft-Goal Conflicts

6.1 Introduction

In Chapter 5, we presented an approach to converting abstract qualities into concrete specifications. Abstract qualities may conflict given certain design models. These conflicts may be difficult to spot in the abstract, and even more difficult to resolve in a controlled manner. By transforming these abstract qualities into concrete specifications based on their design models, we can perform a formal analysis of these specifications and obtain specific information about conflicts within these specifications.

Resolving these conflicts in a controlled manner can be a difficult problem. In this chapter, we present a formal method for the resolution of these conflicts, which allows the designer to more easily analyze and resolve these conflicts in a controlled manner.

To accomplish this task, we leverage work within both the model checking and satisfiability communities. The approach we are taking is to first generate a set of system traces using the models created at design time. Second, we analyze the system traces, using metrics that are tied to the abstract requirements. Third, we generate a set of policies that will guide the system toward the abstract qualities. And fourth, we analyze the generated policies for conflicts using Unsatisfiable-Core (UNSAT-Core) techniques.

6.1.1 Contributions

The main contributions of this chapter are: (1) a method of generating resolution suggestions using different resolution strategies, and (2) validation of our approach through experimentation.

6.1.2 Chapter Outline

The remainder of this chapter is organized as follows. In Section 6.2, we describe our algorithm for generating the UNSAT-core. Resolution strategies are presented in Section 6.3. Section 6.4 presents and analyzes experimental results. Section 6.5 concludes.

6.2 Conflict UNSAT-Core Analysis

An UNSAT-core is a subset of an unsatisfiable Boolean formula, which is in itself unsatisfiable. There has been much work [67] on generating a minimal UNSAT-core, however, this can be a hard problem. UNSAT-core generation is has been used in numerous applications such as the Alloy Analyzer [68], a software modeling tool for the Alloy language.

These UNSAT-cores help strip away useless information when analyzing problems in models. Since a single point of conflict may have large repercussions, it may affect a number of parts of a system. However, it is simply not feasible for a system designer to work with such a large number of conflicts. Thus, it is important to be able to filter and separate information for a system designer to be able to get a better grip on the problem at hand.

An overview of our abstract requirement conflict analysis framework is depicted in Figure 6.1. We take the abstract requirements and link them to metrics. These metrics are usually not domain specific and are measurements over traces of the system that have been generated using the design models. This connection of metrics to abstract requirements, while an important issue, is not the focus of this work. Using the traces, design models, and metrics, we generate supporting policies. These policy sets may conflict with one another. These conflicts signal a conflict in the original abstract requirements with respect to the

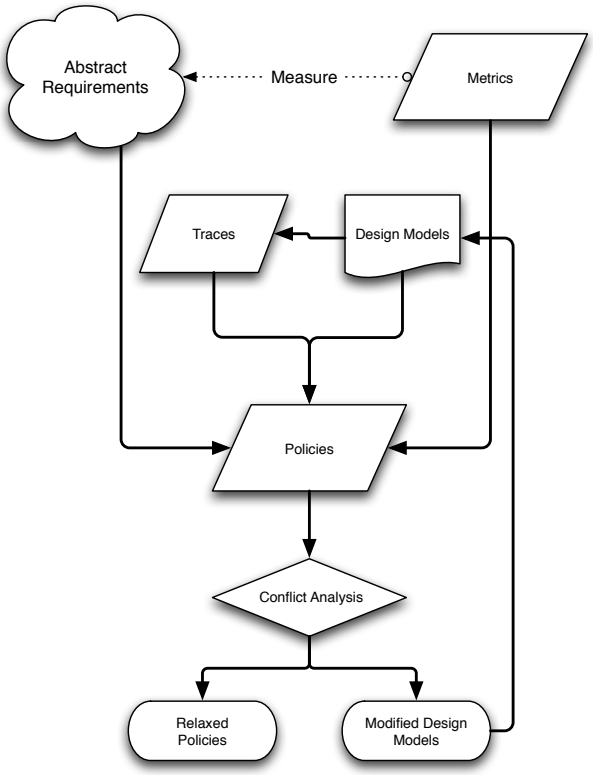


Figure 6.1: Abstract requirement analysis process.

design models. We then take these conflicts to motivate design changes in our models, or to refine the original abstract requirements.

6.2.1 Policy Synthesis and Analysis

Using the same definition as in Chapter 3, we partition the conflict-space into *Definitely Conflicts* and *Possibly Conflicts*. In this work, we will be focusing on the *Definitely Conflicts* space, although it may be easily extended into the *Possibly Conflicts* space.

The policies synthesized by our system are converted into Boolean formulas using the following method: each agent, role, and goal is represented by a Boolean literal. Thus, an assignment is represented as an *and* expression containing a role, an agent, and a goal literal. For example, a synthesized policy is given in Figure 6.2. The first half of the policy represents the condition or guard, while the second half represents the options available

to the system. The conditions in the guard are *and* connected, while the options are *or* connected. Thus, this policy is stating that if we are at a state in our system where $Agent_2$ has achieved the *Pickup area* goal while playing the *Pickuper* role 4 times, $Agent_1$, while playing the *Organizer* role, has achieved the *Divide area* goal once, and $Agent_5$ has achieved the *Vacuum Area* goal once while playing the *Vacuumer* role, then the next assignment must be either $Agent_2$ playing the *Pickuper* role to achieve the *Pickup area* goal, or it must be $Agent_5$ playing the *Vacuumer* role to achieve the *Vacuum Area* goal. The $*$ in the goal parameter represents the wild-card, matching any parameter.

$$
\begin{aligned}
< Agent_2, Pickuper, Pickuparea(*) >: 4 \\
< Agent_1, Organizer, Dividearea(*) >: 1 \\
< Agent_5, Vacuumer, VacuumArea(*) >: 1 \\
=> \\
< Agent_2, Pickuper, Pickuparea(*) > \\
< Agent_5, Vacuumer, VacuumArea(*) >
\end{aligned}
$$

Figure 6.2: CRFCC Generated Policy

To generate the Boolean logic formulas, we maintain a table relating the Boolean literals to the objects in our policies as in Figure 6.3.

Agent	Lit.	Role	Lit.	Goal	Lit.
$Agent_1$	α_1	Pickuper	ρ_1	Pickup area	γ_1
$Agent_2$	α_2	Organizer	ρ_2	Divide area	γ_2
$Agent_5$	α_3	Vacuumer	ρ_3	Vacuum area	γ_3

Figure 6.3: Object to Literal Mapping

For the first assignment in the condition of Figure 6.2, we generate the expression: $\alpha_2 \wedge \rho_1 \wedge \gamma_1$. The entire condition is given in Equation 6.1.

$$\alpha_2 \wedge \rho_2 \wedge \gamma_2 \wedge \alpha_1 \wedge \rho_2 \wedge \gamma_2 \wedge \alpha_3 \wedge \rho_3 \wedge \gamma_3 \tag{6.1}$$

Generation of the options is more complex. Not only must we represent the options of the system, but we also must represent the options the system may not choose. Thus, the options are now split into two parts. The first part containing the original options of the policy, while the second part contains the options that the system does not have.

$$(\alpha_2 \wedge \rho_1 \wedge \gamma_1) \vee (\alpha_3 \wedge \rho_3 \wedge \gamma_3) \tag{6.2}$$

To optimize the analysis of the Boolean formulas, we only include forbidden options from policies that will be active at the same time. The overall Boolean formula for a policy is shown in Equation 6.3.

$$\begin{aligned} &\alpha_2 \wedge \rho_1 \wedge \gamma_1 \wedge \alpha_1 \wedge \rho_2 \wedge \gamma_2 \wedge \alpha_3 \wedge \rho_3 \wedge \gamma_3 \wedge \\ &((\alpha_2 \wedge \rho_2 \wedge \gamma_2) \vee (\alpha_3 \wedge \rho_3 \wedge \gamma_3) \wedge \neg(\theta_1 \vee \theta_2 \vee \ldots)) \end{aligned} \tag{6.3}$$

Where θ_1 and θ_2 are assignments and are of the form $\alpha_x \wedge \rho_y \wedge \gamma_z$ and the remainder is from Equation 6.1 and 6.2.

For a given set of policies, we generate a Boolean formula for each policy and then we connect those formulas using the *and* operator. This formula is then converted to conjunctive normal form (CNF). The CNF formula is given to ZChaff [70], a high-performance SAT solver, which generates the UNSAT-core. Zchaff's heuristic learning is a natural fit for our problem space. Zchaff employs learning heuristics in which conflict analysis plays a large role [71].

ZChaff provides the variables as well as the clauses that are involved in the UNSAT-core. These variables can then be mapped back to the model elements using a table such as in Figure 6.3.

6.3 Resolution Strategies

Now that we can identify conflicts in abstract qualities and find the core of these conflicts we can use various strategies to resolve these conflicts. The strategies used can depend

on the preferences and resources of the system designer. In some systems, the agents and capabilities are fixed, while other system designs may allow for more changes.

The conflict resolution space is partitioned into *Design Changes* and *Requirement Relaxation*. Thus, we have two main ways of solving conflicts. Either by changing the design, e.g. by adding agents, capabilities, and so forth, or by relaxing the requirements, e.g. by not enforcing the abstract requirement in all cases.

Relaxing requirements can be done in various ways. It may be the case that the system designer never meant for the requirement to be so broad in the first place. Through our framework, a system designer can iteratively refine their requirements. This is done by starting with a general requirement and iteratively refining this general requirement by resolving conflicts in the requirements space. For example, if we wish our system to both be efficient and also deliver the best quality products, we may have conflicts in these requirements with respect to our system design and resources available to the system (agents, capabilities, etc.). We can examine the conflicts in these requirements with respect to our system design by looking at the conflicts in the generated policies. For example, we may have abstract requirements related to both efficiency and reliability. However, it may be the case that given our current system design, there is no way for our system to always achieve both of those qualities. In this case, the generated policy sets for reliability and quality will have conflicts.

6.4 CRFCC System Evaluation

Taking the Cooperative Robotic Floor Cleaning Company (CRFCC) described in Section 3.2.2, we used the agent model depicted in Figure 6.4 and the capability failure matrix in Figure 6.5.

The agent model in Figure 6.4 gives a possible set of agents for our CRFCC system. Each agent possesses various capabilities that will make them able to achieve various goals by playing roles. $Agent_3$ possesses *Search*, *Move*, and *Sweep* capabilities. The *Org* capability

is only possessed by $Agent_1$, while the *Move* capability is possessed by all the agents save $Agent_1$. $Agent_2$ also possesses the *Search* and *Pickup* capabilities. *Mop* and *Sweep* capabilities are possessed by $Agent_4$. $Agent_5$ possesses both *Vacuum* and *Sweep* capabilities.

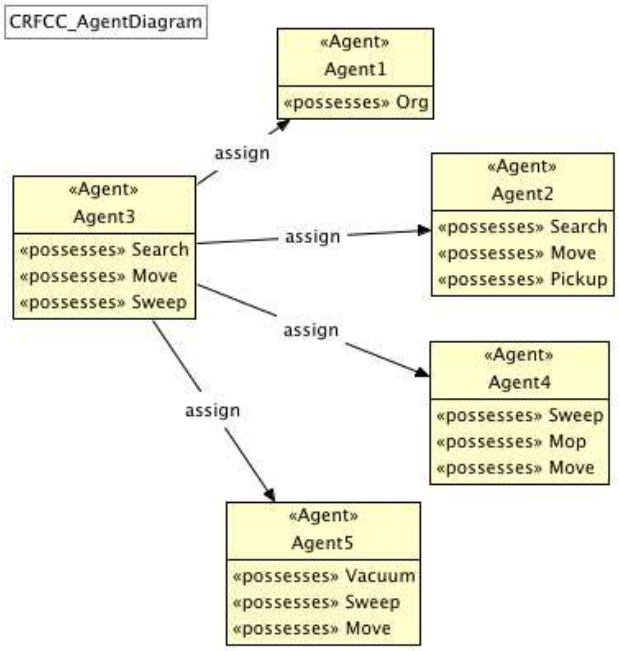


Figure 6.4: CRFCC Agent Model

Given the capability failure matrix in Figure 6.5, we computed reliability policies. Capabilities not listed are expected to have a 0% probability of failure. The capability failure matrix represents a grouping of probabilities that a certain capability will fail given a particular assignment. This assignment can be generalized. For this example, we have generalized the assignment to only consider the agent (ignoring the role, goal, and goal parameter). $Agent_5$'s *Sweep* capability has a 50% chance of failing whenever this agent is assigned to achieve a goal using that capability. $Agent_3$ has a 10% chance of its *Sweep* capability failing when assigned to achieve a goal using that capability. We consider capability failure to be transient. Thus, if a capability fails, it may only be failing in the context of the current agent achievement assignment.

Different agents may produce different quality results in their goal achievements. We use

Capability/Assignment	$Agent_5$	$Agent_3$
sweep	0.5	0.1

Figure 6.5: CRFCC Goal Assignment Choice with Capability Failure Probabilities

a partial order of goal achievement assignments to compare quality of product. Figure 6.6 gives an example partial ordering. Here we can see that $Agent_3$ achieves a higher quality of product than both $Agent_4$ and $Agent_5$ when achieving the *Sweep* goal while playing the *Sweeper* role. Here, the * in the goal parameter, again, represents the wild-card, matching any parameter.

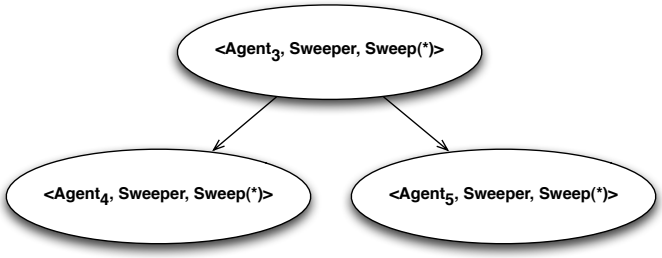


Figure 6.6: CRFCC Quality of Product Ordering

6.4.1 CRFCC Results

For the reliability soft-goal, we produced some 347 policies, which were then condensed down to 10 policies using generalization. For quality, we also produced 347 polices, which condensed down to 10 policies. With these policies we had 19 conflicts.

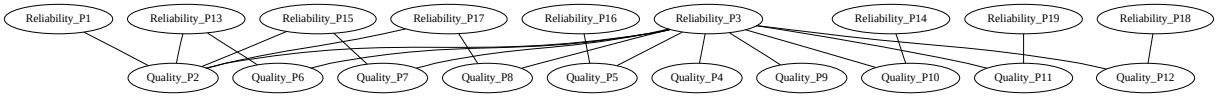


Figure 6.7: CRFCC Policy Conflicts

As can be seen by Figure 6.7, even this very simple example can have many conflicts. In this graph, each node represents a policy, while each edge represents a conflict. Two policies are considered to definitely conflict if their guards cover the same state of the system and the intersection of the both choice sets is empty. In our research, we have found that moderately

sized examples can have an overwhelming number of lines of conflict. This great number seriously impedes a system designer's ability to deal with the conflicts. For this reason, we have turned to UNSAT-core analysis. This helps us strip away unnecessary information and better compartmentalize the different issues in a way that a system designer can more easily handle.

Converting these policies to a Boolean formula created a conjunctive normal form with 15 variables and 2661 clauses. ZChaff easily concluded that the formula was not satisfiable and gave us the UNSAT-core. This UNSAT-core analysis gave us a smaller conflict to consider, namely, the *Sweeper* role, the *SweepArea* goal, and $Agent_4$ *must* be used while *Sweeper* role, the *SweepArea* goal, and $Agent_4$ *must not* be used. This traces back to a quality clause that says $Agent_3$ should be performing this assignment instead of $Agent_4$.

We ran simulations of our organization with different policy configurations. For each setup we varied the number of rooms to clean, while everything else was held constant. At each number of rooms, we made a 1000 runs and took the average as the result.

We ran five sets of experiments: 1. No Policies, 2. Reliability Policies, 3. Quality Policies, 4. Both Policy Sets (No conflict resolution), and 5. Both Policy Sets with conflict resolution. In each set of experiments we measured the number of agent goal achievement failures as well as the number of inferior quality of products produced.

For the 5^{th} experiment, we implemented the policies so that Reliability was always more important than Quality, except when cleaning the floors of a certain client. This client represented 3% of the cleaning in our experiments.

Figure 6.8 presents the Reliability results. The y-axis represents the number of agent achievement failures (lower is better), while the x-axis represents the total number of rooms to clean. We can see that with no policies we get the worst reliability. When we have the reliability policies alone, we achieve perfect reliability, which is not surprising given that we have sufficient agents to achieve this. When we have quality policies only, we do have an improvement in reliability. This is most likely due to $Agent_3$'s lower failure probability than

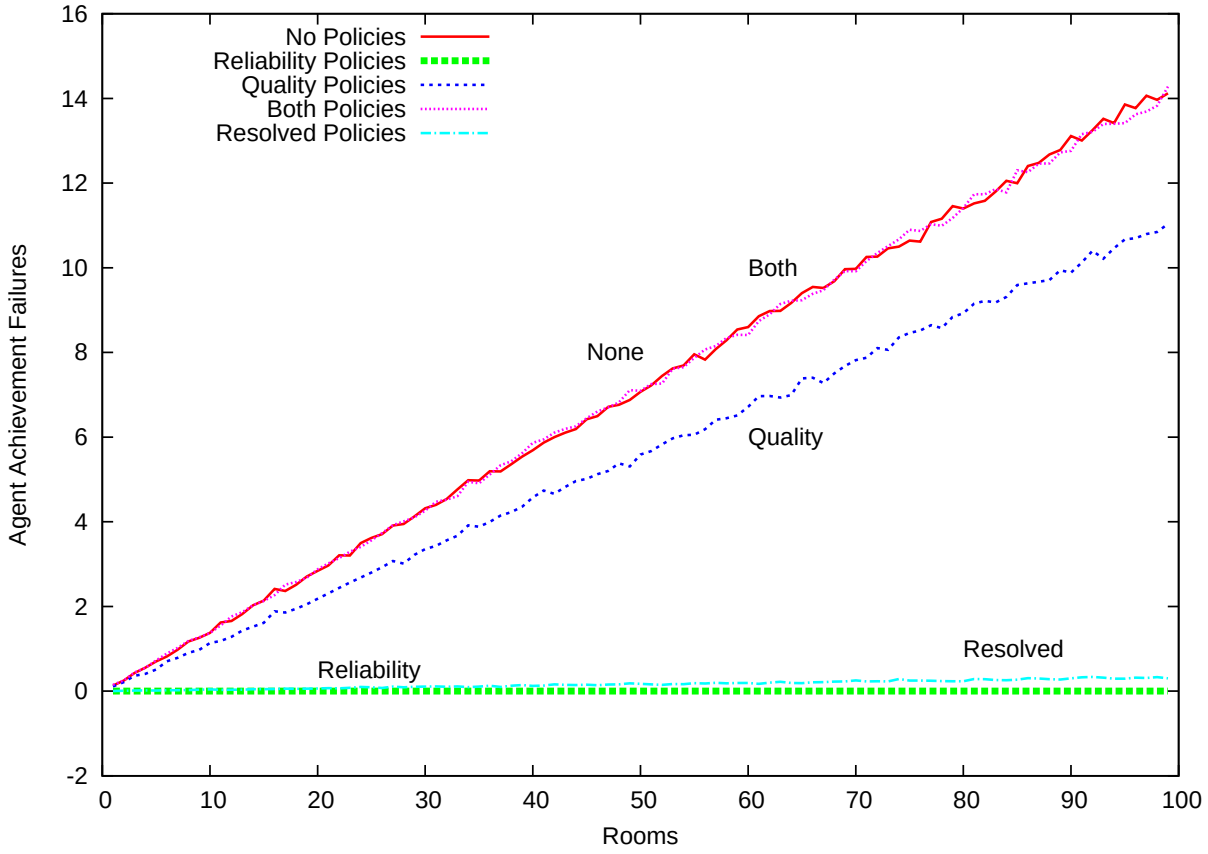


Figure 6.8: CRFCC Reliability Results

$Agent_5$. The interesting point, however, is when we have both sets of policies active at the same time. It turns out this is about the same as having no policies at all since we have so many conflicts within the policy sets. The Resolved line shows very similar performance to the Reliability line, which is what we expect since we usually prefer Reliability over Quality in our conflict resolution.

Figure 6.9 tells a very similar story to the one above. Here, the y-axis represents the number of *inferior* quality products obtained (lower is better), while the x-axis again represents the total number of rooms to clean. In this result, we achieve the worst performance when we have Reliability policies alone. The best performance is observed when we have Quality policies alone. Again, this is not surprising, given the agents in our models. We see a very familiar story with No policies and Both policies. They perform nearly identical due

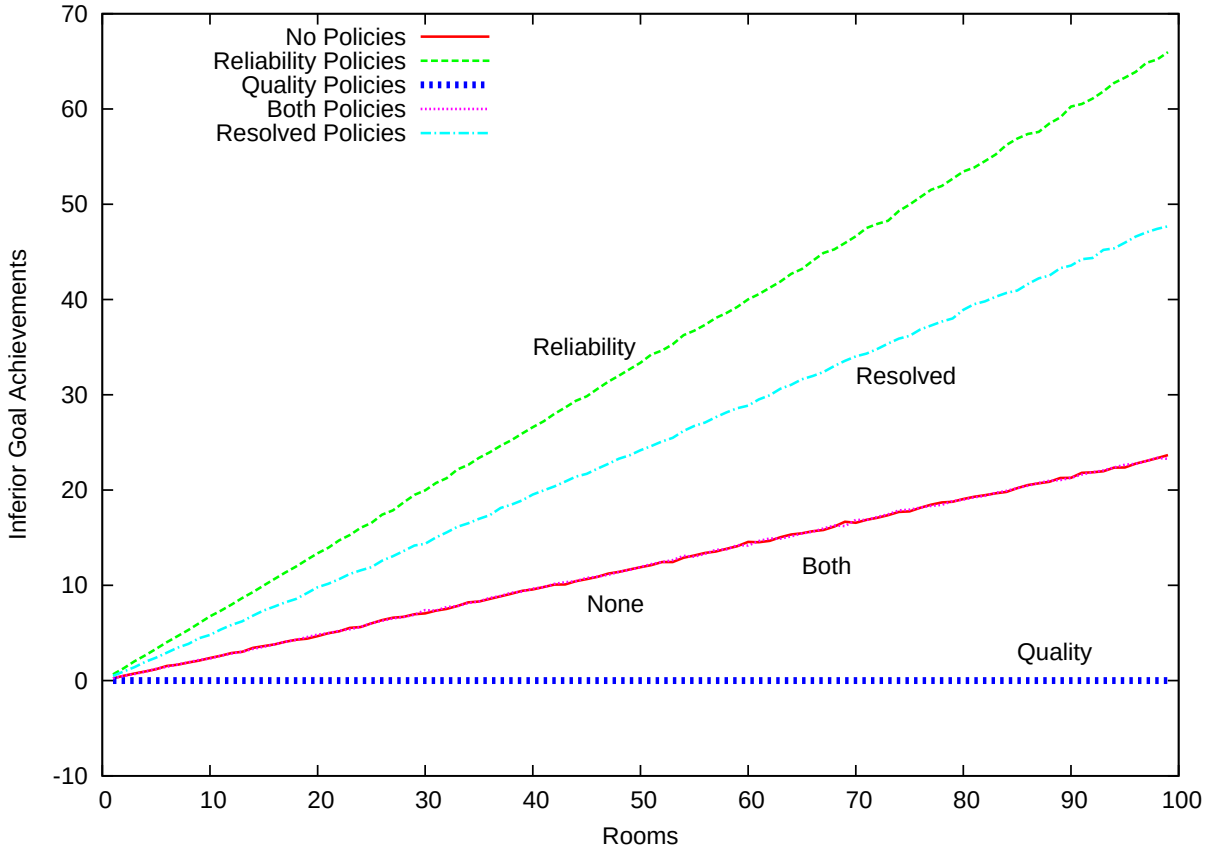


Figure 6.9: CRFCC Quality Results

to the conflicts. The Resolved line shows that we achieved higher quality than the Reliability alone, but not as high as the No Policies line. This is due to preferring Reliability over Quality in most cases.

Clearly, when we have both sets of policies in effect at the same time, we do not obtain the desired results. This is because of the conflicts. These conflicts need to be resolved in order to stabilize the qualities the system exhibits. We may do this in two different ways, one would be to change the design of the system, that is, to add or modify agents. Clearly, the issue at hand is that while $Agent_3$ produces a higher quality product, $Agent_4$ is more reliable. This is given by the UNSAT-core analysis. One way to resolve this could be to make $Agent_3$ reliable. This, however, is not always feasible.

Another way to resolve this conflict could be relaxing our soft-goals. A natural way to

relax our soft-goals is to create a partial order of preference using the goal parameters. For example, in our floor cleaning system, if the floor belongs to a certain type of customer, we will prefer quality over reliability, otherwise we will always prefer reliability. This gives the system designer control over how the qualities are relaxed. Future tools could give this option to a system designer.

6.5 Conclusions

Soft-goals are an important part of system design. However, little work has been done on the formalization and analysis of soft-goals. We view soft-goals as abstract requirements. These abstract requirements can be made concrete by creating a relationship between the abstract requirements and metrics over the system traces. These metrics measure aspects of the system over traces that have been generated on the system models. The measurements are used to generate guiding policies for the system. These policies, however, may have conflicts. This is indicative of conflicts within the original soft-goals with respect to our current system design.

We have taken an important step to formalize the analysis of these soft-goals and have shown that the implementation of these soft-goals can have a great impact on the qualities exhibited by the system. We have also shown how we can automate resolution suggestions using UNSAT-core analysis.

Our work has some important limitations. One possible area of concern is our use of model checking. It is well known that model checking often suffers from state-space explosion. This could also affect our analysis. However, since we are already working with an abstraction of the system (the design models), and not the actual code, this is not too much of a concern. Another area of concern is the linking of soft-goals to metrics. This has the potential to be a difficult task and may not always be trivial. There is no automated method of doing this.

Chapter 7

Conclusions

7.1 Guidance and Law Policies

Policies have proven to be useful in the development of multiagent systems. However, if implemented inflexibly, situations such as described in [51] will occur (a policy caused a spacecraft to crash into an asteroid). Guidance policies allow a system designer to guide the system while giving it a chance to adapt to new situations.

With the introduction of guidance policies, policies are an even better mechanism for describing desired properties and behaviors of a system. It is our belief that guidance policies more closely capture how policies work in human organizations. Guidance policies allow for more flexibility than law policies in that they may be violated under certain circumstances. In this thesis, we demonstrated a technique to resolve conflicts when faced with the choice of which guidance policies to violate. Guidance policies, since they may be violated, can have a partial ordering. That is, one policy may be considered more important than another. In this manner, we allow the system to make better choices on which policies to violate. Traditional policies may be viewed as *law policies*, since they must never be violated. Law policies are still useful when the system designer never wants a policy to be violated–regardless of system success. Such policies might concern security or human safety.

Policies may be applied in an OMACS system by constraining assignments of agents to roles, the structure of the goal model for the organization, or how the agent may play a

particular role. Through the use of OMACS, the metrics described in [35], and the policy formalisms presented here, we are able to provide an environment in which a system designer may formally evaluate a candidate design, as well as evaluate the impact of changes to that design without deploying or even completely developing the system.

Policies can dramatically improve run-time of reorganization algorithms in OMACS as shown in [40]. Guidance policies can be a way to achieve this run-time improvement without sacrificing system flexibility. The greater the flexibility, the better the chance that the system will be able to achieve its goals.

Guidance policies add an important tool to multiagent policy specification. However, with this tool comes complexity. Care must be taken to insure that the partial ordering given causes the system to exhibit the behavior intended. Tools which can visually depict the impact of orderings would be helpful to the engineer considering various orderings.

7.2 Learning Policies

Multiagent systems can become quite complex and may be deployed in environments not anticipated by the system designer. Furthermore, the system designer may not have the resources to spend on hand-tuning the system for a particular deployment. With these issues in mind, we have developed a method to create self-tuning multiagent systems using guidance policies.

Using a variation of Q-Learning, we have developed an algorithm that allows the system to discover policies that will help maximize its performance over time and in varying environments. The use of guidance policies, helps remove some of the traditional problems with using machine learning at the organization level in multiagent systems. If the learner creates bad policies, they should not prevent the system from achieving its goal (although they may degrade the quality or timeliness of the achievement). In this way, our approach is 'safer' and thus we can use a simpler learner.

In the experiments we conducted, the system was able to adapt to multiple agent goal

achievement failures. It was able to cope with randomized and history-sensitive failures. The learner was able to discover guidance policies which, in every case, caused our systems to perform better on the order of a magnitude when faced with these failures.

Since we are taking the approach of always trying to avoid bad states, there is the question of whether our approach will possibly drive the system away from the optimal state in certain diabolical cases. The argument is that in order to get to the best state, we must pass through some bad states. To address this, we need to look at what is being considered as a bad state and if it is possible for there to be a high-scored state that can only be reached through a bad state. In the experiments we have performed, bad states corresponded to agent goal achievement failures. Using agent goal achievement failures as the scoring method of our states, it is possible that you must pass through a bad state in order to get to an end state with the highest score. But, since the score is inversely proportional to agent goal failures, we will have to go through a bad state in any case. We argue that since our score is monotonic, our algorithm should be able to drive toward the best scored state even in the diabolical case that you must go through a bad state. This would require that we order our learned guidance policies using the more-important-than relation by score.

The usage of guidance policies allow for retention of useful preferences and automatic reaction to changes in the environment. For example, there could be an agent that is very unreliable, thus the system may learn a policy to not make assignments to that agent, however, the system may have no alternatives and thus must use this agent. "We don't like it, but we deal with the reality."–that is until another agent that can do the job joins the system.

7.3 Abstract Qualities

We have provided a framework for stating, measuring, and evaluating abstract quality requirements against potential multiagent system designs. We do this by generating policies

that can be used either as a formal specification, or dynamically within a given multiagent system to guide the system toward the maximization (or minimization) of the abstract quality constraints. These policies are generated offline, using model checking and automated trace analysis.

Our method allows the system designer to see potential conflicts between abstract qualities that can occur in their system. This allows them to resolve these conflicts early in the system design process. The conflicts can be resolved using an ordering of the qualities which can be parametrized on domain specific information in the goals. They could also cause a system designer to decide to change their design to better achieve the quality requirements. It is easier to make these changes in the design than in the implementation.

These policies can be seen to guide the system toward the abstract qualities as defined in the metrics. Our experiments showed significant performance, quality, and reliability increases over a system using the same models, but without the automated policy generation.

7.4 Soft-Goal Conflicts

Soft-goals are an important part of system design. However, little work has been done on the formalization and analysis of soft-goals. We view soft-goals as abstract requirements. These abstract requirements can be made concrete by connecting them to metrics. These metrics measure aspects of the system over traces that have been generated on the system models. The measurements are used to generate guiding policies for the system. These policies, however, may have conflicts. This is indicative of conflicts within the original soft-goals with respect to our current system design.

We have taken an important step to formalize the analysis of these soft-goals and have shown that the implementation of these soft-goals can have a great impact on the qualities exhibited by the system. We have also shown how we can automate resolution suggestions using UNSAT-core analysis.

Our work has some important limitations, including our use of model checking, which

often suffers from state-space explosion. However, as we are dealing with an abstraction of the system, and not code, this is of less concern. Another area of concern is the linking of soft-goals to metrics, which has the potential to be non-trivial.

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Appendix A

Policy Format

A.1 XML Schema

```
<!ELEMENT policies (policy*)>
<!ELEMENT policy (guard, constraint)>
<!ELEMENT guard (state*)>
<!ELEMENT constraint (assignment+)>
<!ELEMENT state (assignment, count)>
<!ELEMENT count (#PCDATA)>
<!ELEMENT assignment (goal, role, agent)>
<!ELEMENT goal (name, parameter)>
<!ELEMENT name (#PCDATA)>
<!ELEMENT parameter (#PCDATA)>
<!ELEMENT role (#PCDATA)>
<!ELEMENT agent (#PCDATA)>
```

Figure A.1: Policy DTD.

Appendix B

Object Models

B.1 Base Classes

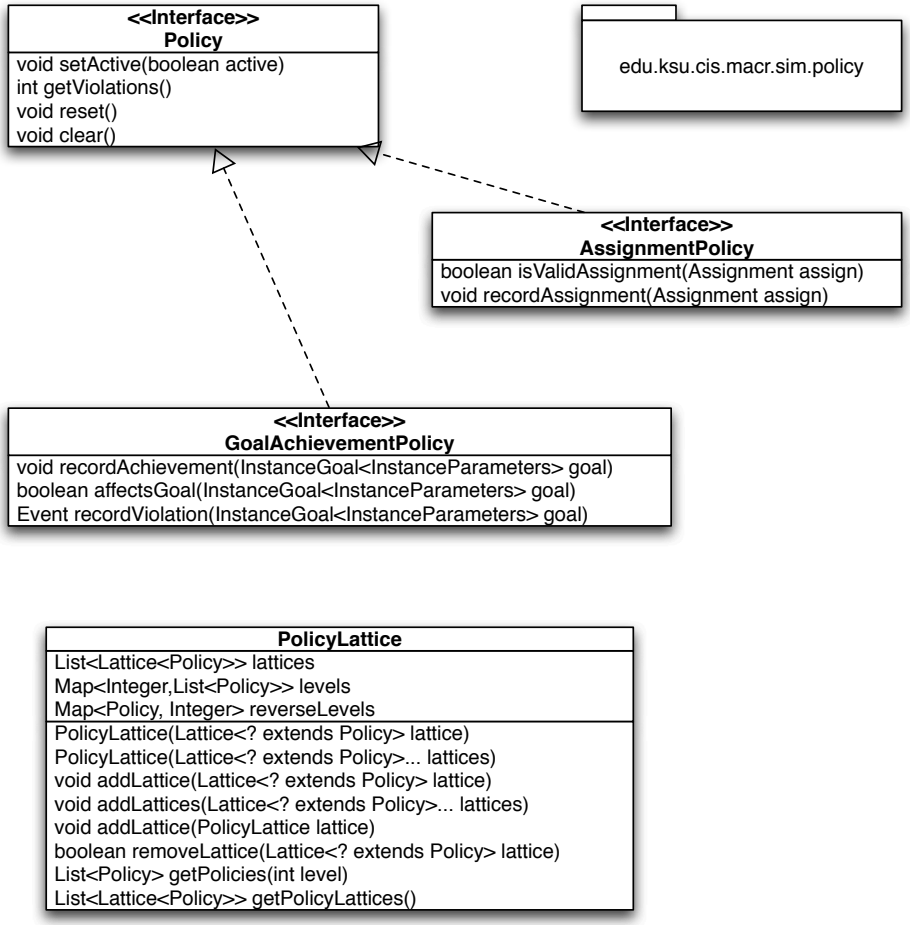

Figure B.1: Base Policy UML Diagram.

Figure B.1 gives the basic model for our policies. The Policy Interface specifies basic methods used in all policies. The *setActive* method allows the simulation engine to disable or enable the policy.

B.2 Policy Learning

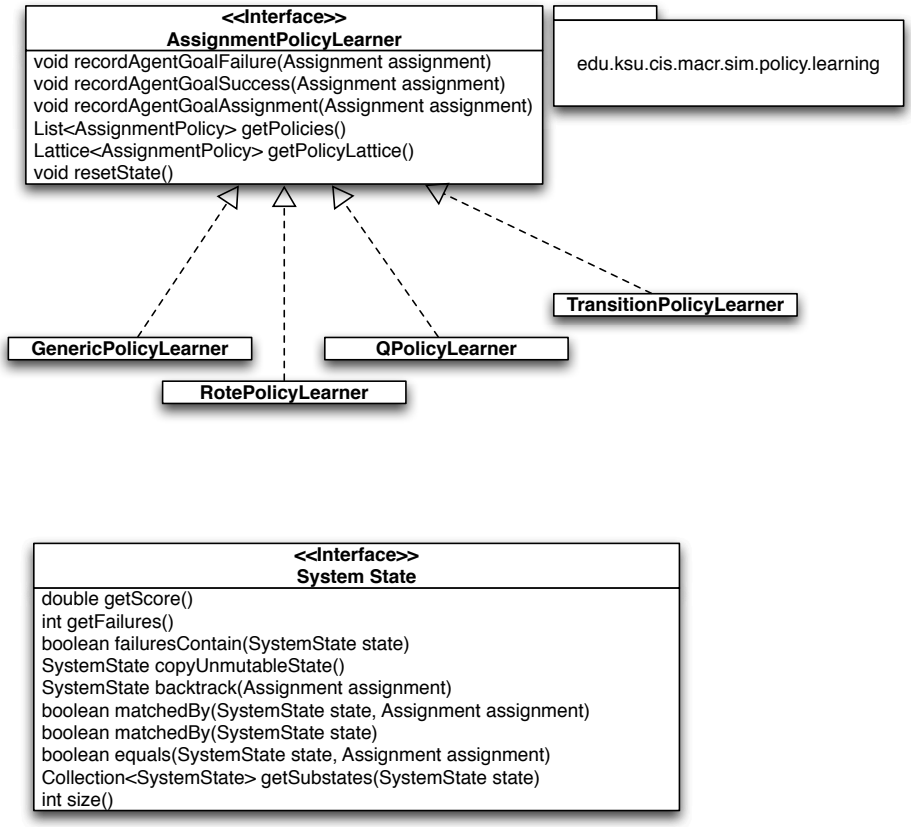

Figure B.2: Policy Learning UML Diagram.

We learn assignment policies as shown in Figure B.2. Using the system state, we experiment with several different learning implementations.

B.3 Trace Generation

Trace generation and analysis requires several basic data structures. Figure B.3 gives the base classes used to represent and manipulate system traces.

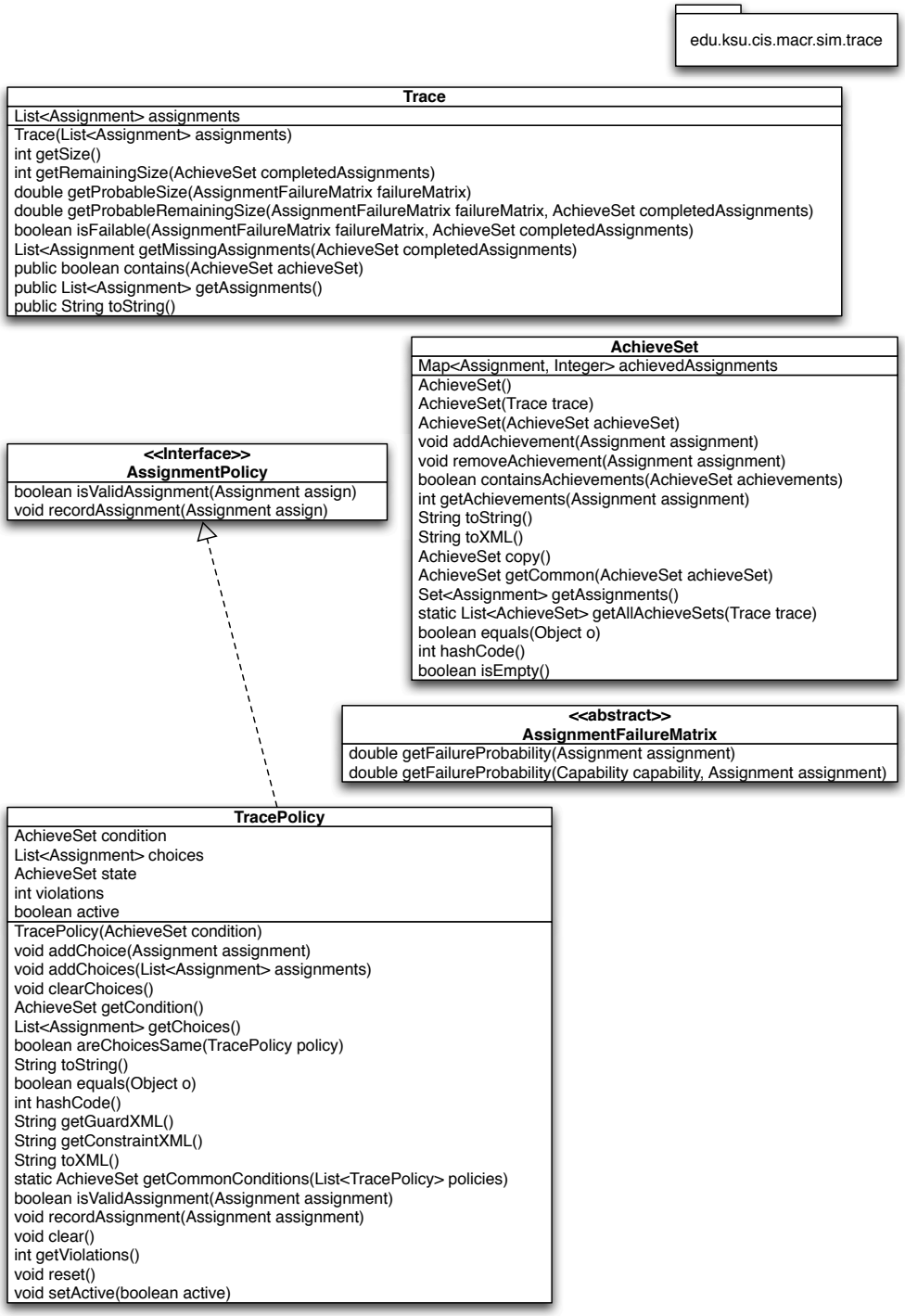

Figure B.3: Policy Trace Base UML Diagram.

In Figure B.4, we depict the policy analysis mechanism. We have a general statistical analysis class as well as a class for each quality.

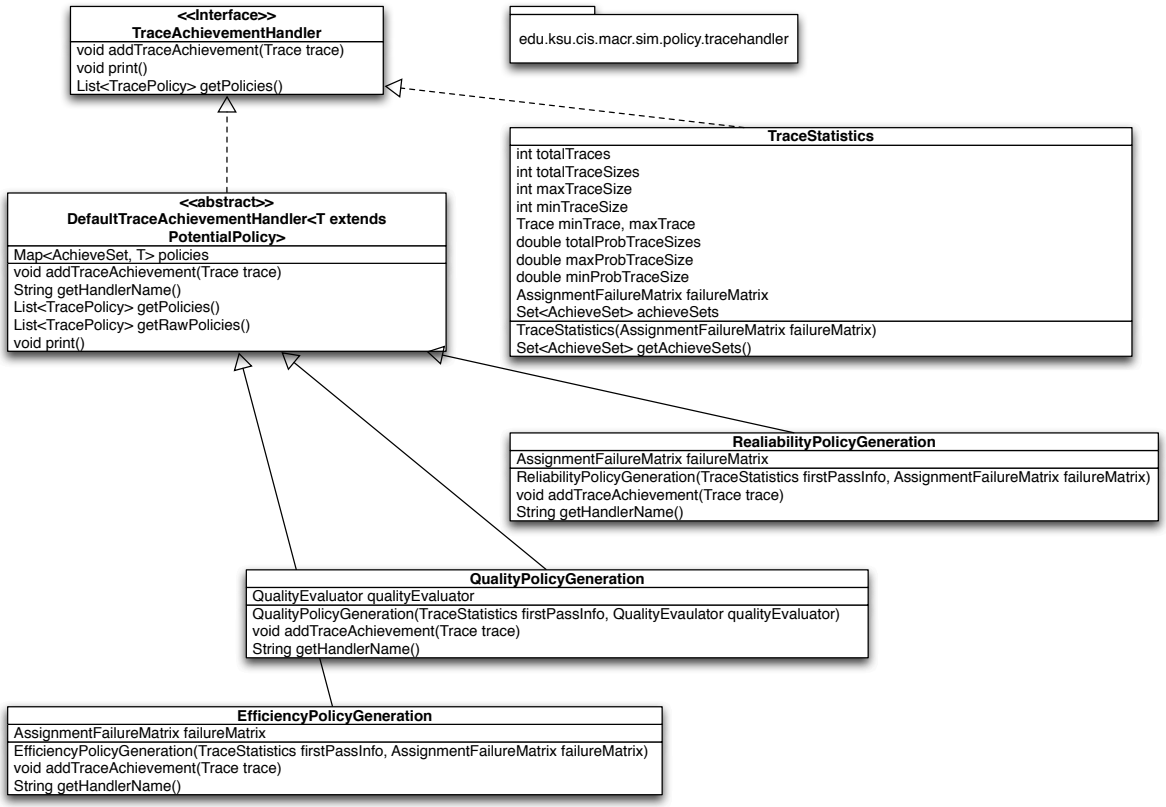

Figure B.4: Policy Trace UML Diagram.

Figure B.5 gives the policy generation and parameter abstraction structures.

B.4 Conflict Analysis

Basic SAT structures and the mechanism to convert our policies to Boolean formulas is shown in Figure B.6.

B.5 Simulation

The simulator uses a set of models to mimic the running of a system based on the engineering design models. The core simulator and models required are depicted in Figure B.7.

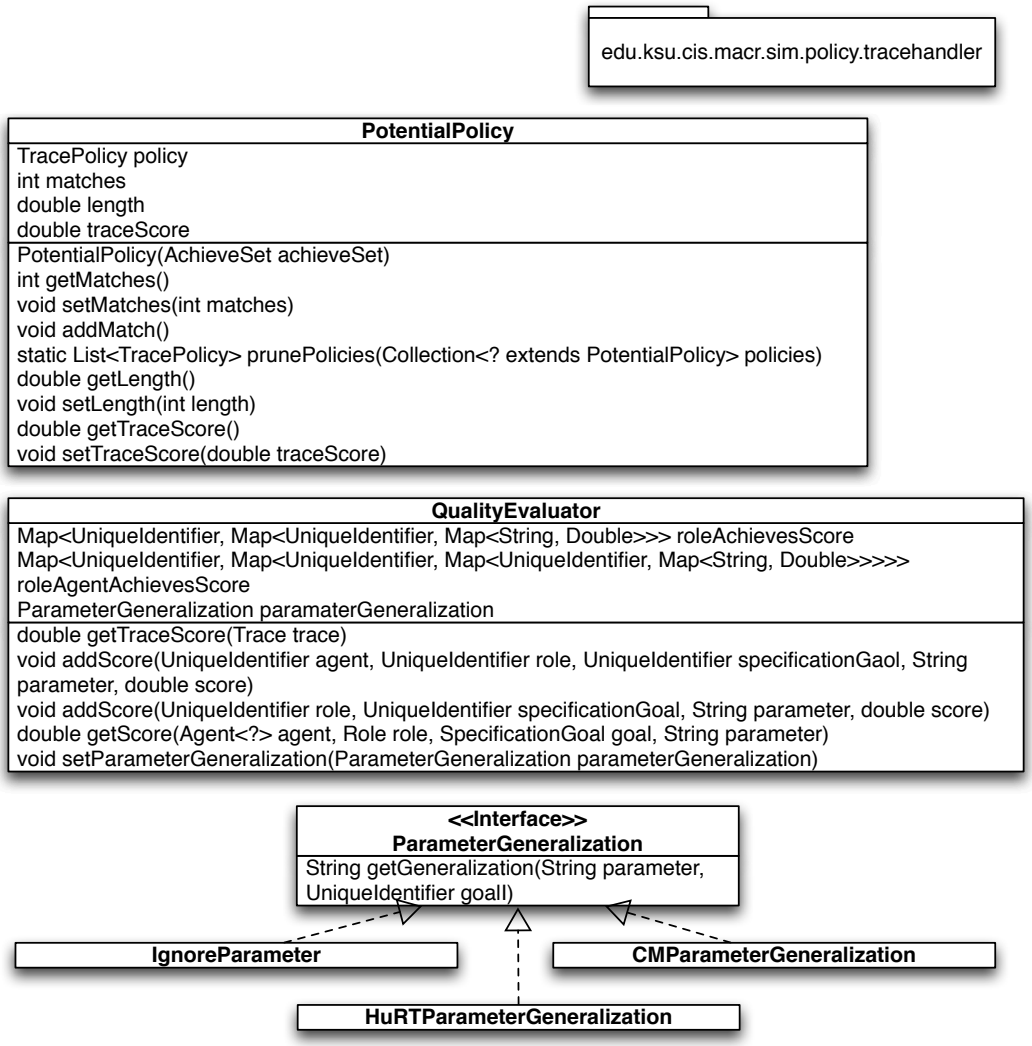

Figure B.5: Policy Generation UML Diagram.

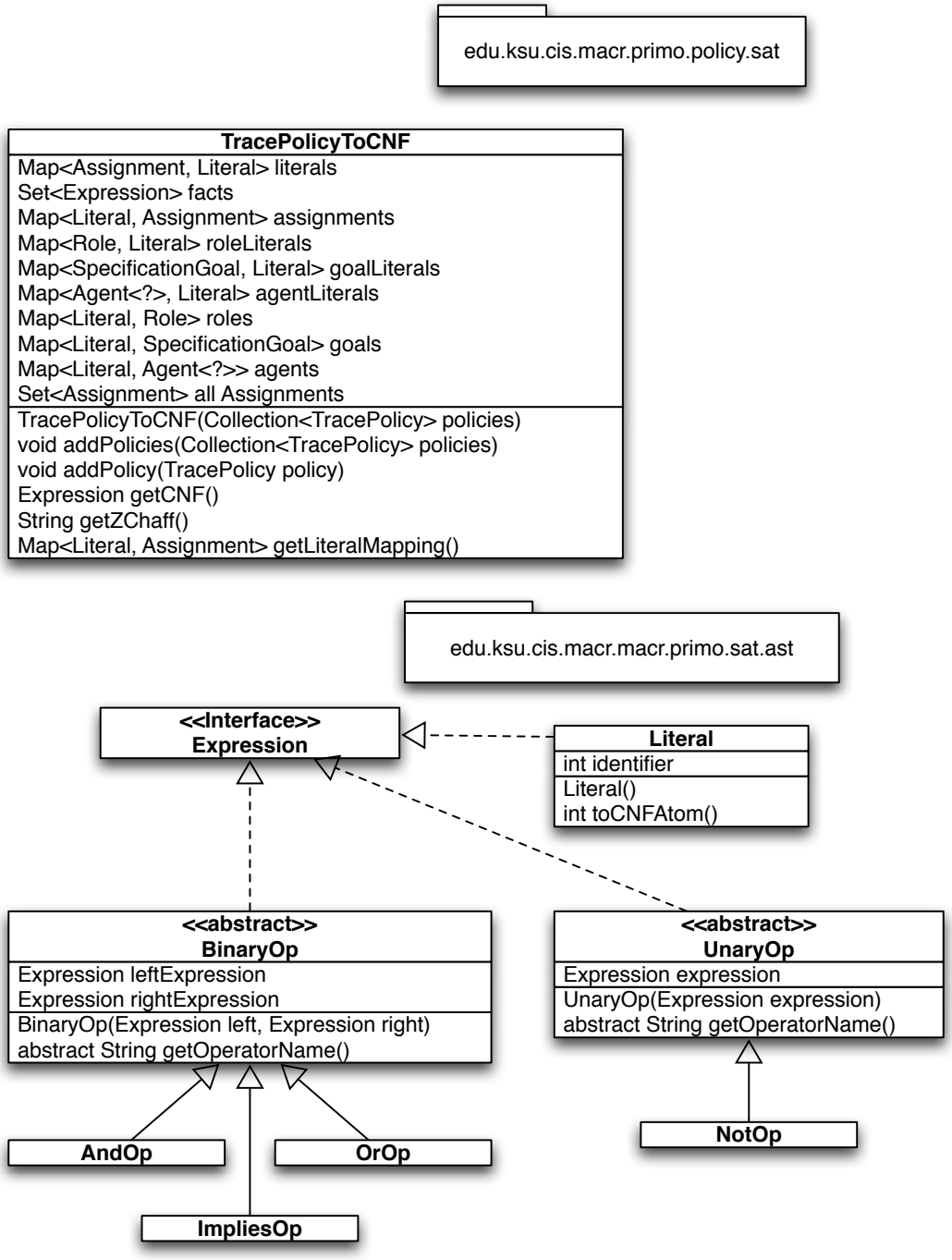

Figure B.6: Policy Trace SAT UML Diagram.

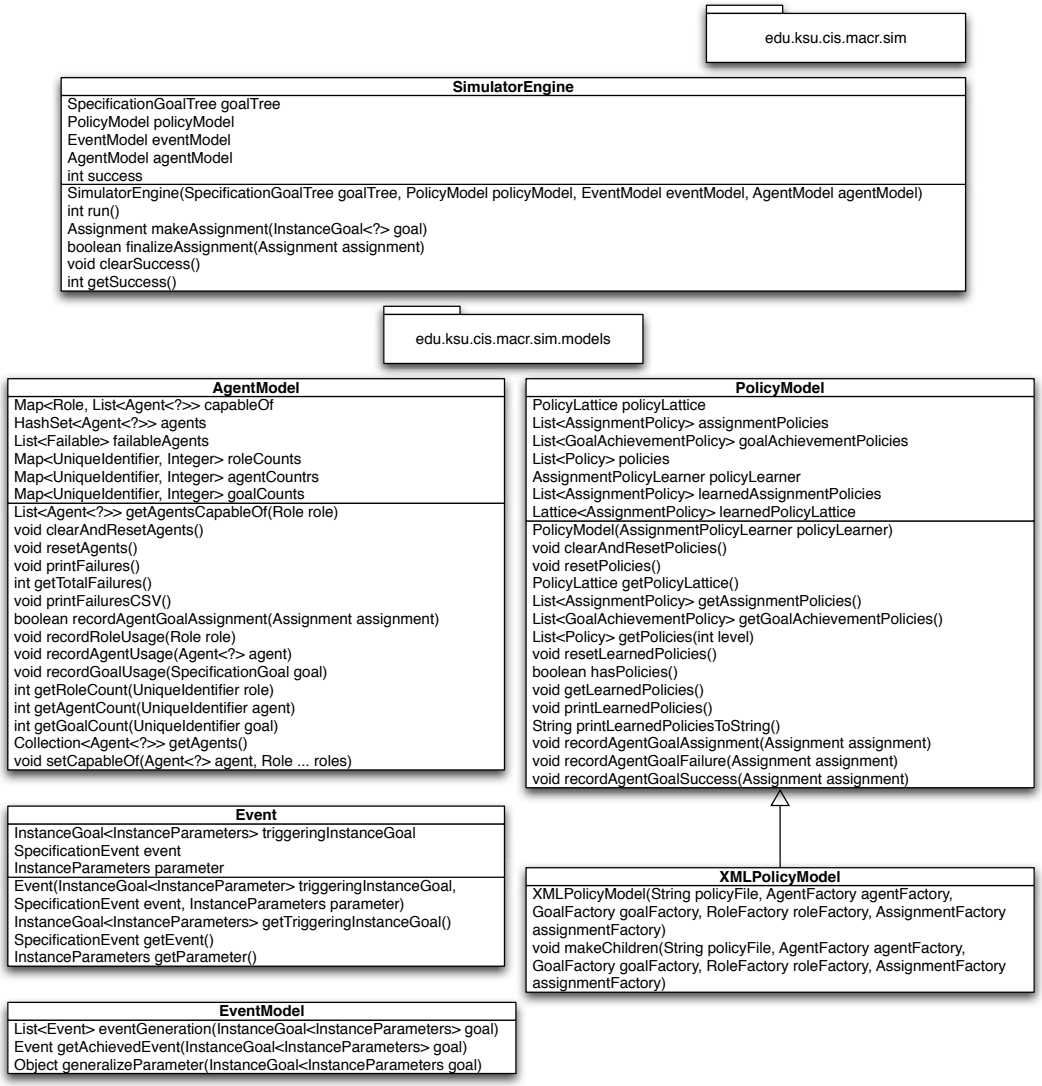

Figure B.7: Core Simulator and Models.

Appendix C

Information Flow Specification and Checking

C.1 Introduction

The Multiagent Systems (MAS) paradigm has quickly become popular for designing medium and large scale systems. Various methodologies [11, 15, 19, 31, 72, 73] have been constructed to aide a designer in constructing systems in a multiagent fashion.

Security, however, has not yet been a consideration in many of the various MAS methodologies currently in use [74]. As multiagent systems become more pervasive, the greater the need to engineer them with security from the ground up. Object-oriented programming has brought many new opportunities to design security in computer software (e.g. Java security policies [75]). MAS, also, brings with it many new opportunities for security. Traditional security concepts such as information flow may be carried over to MAS. Carrying over these security concepts allow for a higher level specification and reasoning about the security concepts.

In this chapter, we focus on Organization-based Multiagent Systems Engineering (O-MaSE) [73], and in particular the Organizational Model for Adaptive Computational Systems (OMACS) metamodel [76]. O-MaSE allows us to build multiagent systems that are compliant with OMACS. We extend O-MaSE with the notion of access control. This extension allows designers to set design time constraints on access to resources and properties

of data within the system. We also give a specification for information flow between various components of an OMACS model. Although we are using a specific multiagent system design methodology, our work should be applicable to many other methodologies. There is work to generalize the current methodologies to O-MaSE [22].

The contributions of this chapter consist of providing a way to specify certain security constraints during design time for a multiagent system as well as providing a way to reason about these specifications in an automated fashion. The content of the paper is arranged in the following manner. First we give some background on security in multiagent systems. Policies for multiagent systems are then briefly introduced. After the introduction of policies, an example to illustrate our ideas is given. Security policies are then introduced, after which access control policies are defined and explained in the context of the example. Information flow policies are defined and also explained in the context of the example. The next section gives a formal method to reason about the security policies defined above and illustrates this with an example. This formal method is then automated using a SAT solver. Finally, the conclusions are given and limitations is presented.

C.2 Background

Much work has been done in the area of multiagent systems. There have been many proposed methodologies for the design and construction of multiagent systems [11, 15, 19, 31, 72, 73]. There has also been some work on securing these types of systems. There has not been much work, however, on integrating security deeply within the design model of multiagent system methodologies [74].

C.2.1 Security in multiagent systems

Security is just beginning to be considered in multiagent systems. Fortunately, much can be borrowed from existing security work in both traditional systems as well as distributed systems.

There has also been some work done in security for open multiagent systems, such as the semantic web [27]. In their paper, Kagal et al. proposed a language to allow decentralized and dynamic security policies for the semantic web. They also define a concept of meta-policies, which specify what to do in the case of policy conflicts—since the policies are dynamic and distributed, the chances of policy conflicts are high.

Other work for open systems has been to randomize policies in order to prevent adversaries from guessing a system or agent's routine [28]. If an agents' actions can be predicted, an adversary may be able to subvert certain security measures. Imagine that an agent patrols a camp. If the agent always completes a round in the same time and always begins a round at the same time, an adversary may be able to predict when an agent would be in a position to miss an approaching enemy. In Parchuri et al.'s paper, they give three algorithms for randomizing policies in order to curb an adversary's ability to predict the system's behavior.

Various enforcement mechanisms have been researched. Shneider [77] defines three types of security policies: 1. Access control; 2. Information flow; and 3. Availability. He then goes on to show how these policies may be enforced by execution monitoring and how automata can be used in that enforcement.

Some runtime as well as static analysis enforcement mechanisms have been proposed. In their paper, Kagal et al. [78] give a language (Rei) and enforcement mechanism (Vigil) for security policies. This language uses the notion of *speech acts* to communicate security requests as well as other security related queries. Their policy engine, Vigil, does execution monitoring to ensure that agents follow security policies.

Runtime or execution monitoring enforcement mechanisms initially had shortfalls, namely that they could not base decisions on possible future executions [77]. This was overcome by Ligatti et al. with their introduction of *edit automata* [79]. Edit automata allow the system to force specific actions. For instance, imagine we have the policy that *a file must always be closed after it is opened*. In traditional run-time monitoring, you cannot decide whether

or not to allow the opening of the file because you don't know if it will be closed properly later. With edit automata, you may inject the file close command, if the code is ever about to violate the policy. Thus, if the code decides to terminate before closing the file, the edit automata simply injects the file close command before the exit.

C.3 Policies in O-MaSE

Policies constrain a system. They are used to cause the system to exhibit certain properties. Policies may be defined in various ways. For example, first order logic may be used. Some policies rely heavily on domain specific knowledge. This makes it important to have an ontology defined by your domain model [41].

Policies may affect assignments of an agent to play a role to achieve a particular goal (assignment policies). For example, *no agent may play more than one role at a time.* Assignment policies are one of the most common policy types in O-MaSE. These policies will limit the system's options in possible assignment combinations. Without any explicit policies, the only limitation to assignments in O-MaSE is that the agent must be capable of playing the role we wish to assign it. Often though, we wish to place further constraints on assignments. For example we might want to state that a certain agent cannot play two specific roles at the same time. These type of policies are very prevalent in human societies as well as agent societies.

Policies can also affect how roles may be played, for instance the policy *when an agent moves down the sidewalk, it always keeps to the right* (role behavioral policy). They may affect the structure of the various models, such as how the goal model must be constructed (goal model behavioral policy), or how the role model should behave (organizational behavioral policy).

For this work, we will use both plain English and first order logic to describe our policies. The security policies defined in this paper are simple enough that temporal operators are not needed (since they are expected to always hold). In more sophisticated policies, one

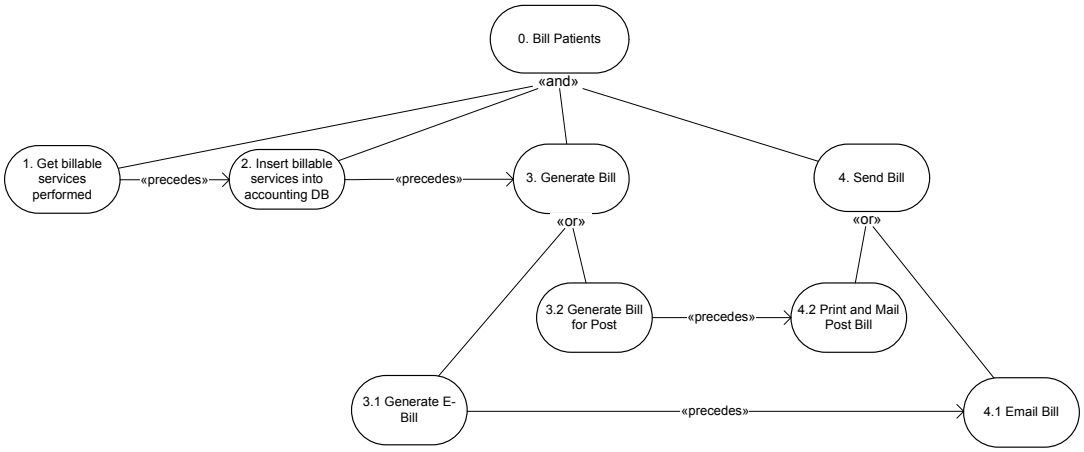

Figure C.1: Medical Billing System Goal Model.

may need the power of Quantified Regular Expressions (QRE) or Linear Temporal Logic (LTL) [43].

C.4 Medical Billing System

In order to illustrate the security properties we wish to define and enforce, we will be using an example of a medical billing system. This system is responsible for billing patients of a doctor's office or hospital. It provides two different methods of receiving a bill, through post mail and through electronic mail. This example will allow us to illustrate two security concerns: *access control* and *information flow*.

The GMoDS goal model of the system is given in Figure C.1. The top level goal is to bill the patients. The leaf goals, *Get billable services performed, Insert billable services into accounting database, Generate E-Bill, Generate Bill for Post, Print and Mail Post Bill, and Email Bill*, must be *achieved* by a *role*, as is required by O-MaSE. This system is actually part of a larger system. Thus the top level goal in this system would be *triggered* for each bill.

A standard O-MaSE role model describes the roles of a system, which includes what goals each role may achieve as well as the interactions between roles (as protocols). We have

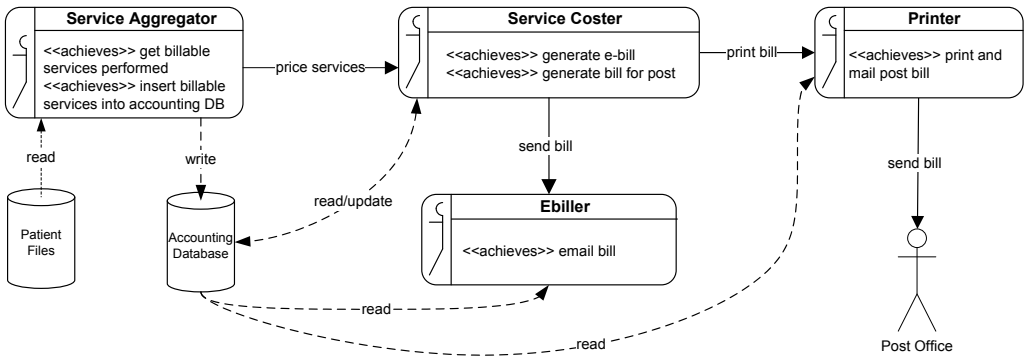

Figure C.2: Medical Billing System Role Model.

augmented this role model with the resources accessed by an agent playing a role as shown in Figure C.2. We have created roles, *Service Aggregator, Service Coster, Ebiller, and Printer*. Each role may *achieve* one or more goals. The solid lines between roles represent interaction between roles or external actors, while dashed lines represent interaction between a role and a resource. It is important to capture the interaction between agents and resources as well as interactions between agents so that one can verify that the design follows the security policies that have been constructed. The text on the dashed lines as well as the arrows indicate how the role is interacting with the resource. In this example, we use *read, write, and update* to represent when an agent obtains data from the resource, places new data into a resource, and updates existing data in a resource, respectively. Each solid line represents an interaction between roles (i.e. a protocol), the arrowhead represents who initiates the interaction. In this example, the agent playing the *Service Aggregator* initiates an interaction with the agent playing the *Service Coster* role.

Agents may be assigned to multiple roles to achieve multiple goals, as long as they are *capable* of playing the roles and there is no policy that would prevent the assignment. Roles may in turn *achieve* multiple leaf goals. This means that an agent may be pursuing multiple goals at the same time.

One of the interactions shown between roles is *price services*. The protocol for this interaction is given in Figure C.3. This protocol specifies that a single message is sent from

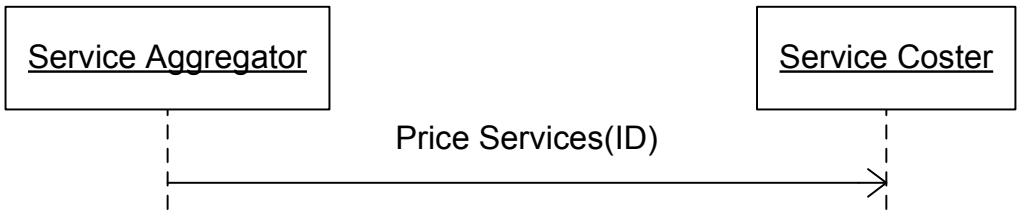

Figure C.3: Price Services Protocol.

the agent playing the *Service Aggregator* role to the agent playing the *Service Coster* role. This message contains the ID that the *Service Coster* must price.

C.5 Security Policies

There are many different aspects to security in multiagent systems. Three important security concepts are *access control*, *information flow*, and *availability* [77]. Access control has been well studied with regard to various things such as file systems. Access control is a restriction on agents to perform certain operations on certain resources. Information flow, also, has been well studied in regard to program execution and ensuring that *high* variables do not flow to *low* variables. Information flow also is concerned with restricting access, but the information may not be simply received from a resource. Availability refers to keeping agents from restricting access to resources, e.g. protecting against a denial of service (DOS) attack.

Since policies are constraints on a system, security policies are, therefore, those policies that impose certain security constraints on the system. Because security is a constraint on the system, it is natural to categorize security constraints as policies.

C.5.1 Access Control Policies

Access control is usually the first type of security considered in most systems. Whenever one 'logs into' a computer, unlocks their home, or enters their car, they deal with *access*

control. Access control can be the mechanism or procedure that ensures only authorized entities make an authorized access of some resource. In multiagent systems, a system designer wants to ensure that only certain agents while playing particular roles may access a resource in a specific way. The designer must be able to specify the types of access as well as the requirements to have such access to the resource. For example, if you don't have a 'top secret' clearance level, you may not access resources marked 'top secret.' You also do not want injection of information that you may consider untrustworthy. For example, you would not want a bank patron to submit tax filings for the bank.

It is important to note here that access control is not just about controlling access to data. Access control may be employed whenever one needs to restrict access to any type of resource. For example, one might imagine that there is a resource that initiates some action on the environment. Access to this resource may also be controlled by a security policy. In this paper, however, we will concentrate on resources that contain data. Other resources can easily be modeled by removing the data properties aspect.

The goal is to identify the resources, the properties of the data that might be part of the resources, the primitive operations that are related to the properties under consideration of the data the resource may contain, and the desired access constraints as relations between agents, roles, primitive operations, and the data properties.

In the role model shown in Figure C.2, high level relationships between resources and roles are given. These constraints may also be captured in an access control matrix [80] as depicted in Figure C.4. If a cell is blank, it means that the role has no access to the resource in that column. The primitive operations in this example are defined as: *Read, Write,* and *Update*. These are the most commonly used operations. More domain specific operations may be defined for a specific system. If an access is not specified in the access control matrix for a particular role on a particular resource, it means that the agent playing this role **may not** have this access on that resource. Role-based access control (RBAC) [81] is a well established method of specifying access control and fits quite naturally within the

Roles	Resources	
	Patient Files	Accounting Database
Service Aggregator	Read	Write
Service Coster		Read/Update
Ebiller		Read
Printer		Read

Figure C.4: Medical Billing System Access Matrix.

Roles	Resources	
	Patient Files	Accounting Database
Patient(x)	readPatient(x)	

Figure C.5: An Access Matrix with a parametrized role.

MAS world.

The resource access matrix, in this example, is only specifying relationships between roles and resources, but in some instances more sophisticated access control may be required. For example, you may want to parametrize a role on an agent. In the examples here, if no agent parameter is given to the roles, the rule applies for all agents. Thus, these access controls apply to whomever may be playing the particular roles. In a more sophisticated system, one might want to allow a person playing a *Patient* role to be able to read their own medical records, but not allow all agents playing the *Patient* role to read all medical records. It is important, therefore, to identify the needed primitive access operations as well as defining the correct parameter and scope for the parameters. In this example one might define a $readPatient(x)$ operation, and then in the access control matrix parametrize the role *Patient* with x. This is illustrated in Figure C.5.

Something to note here is that while an Access Matrix defines what roles/agents *are allowed* to access, the Role Diagram specifies what roles *will* access. This distinction is important as the Role Diagram will be used later to validate security policies that a designer has written. Imagine that a designer builds an access control matrix by consulting the businesses operation practice guidelines as well as state law, e.g. Health Insurance Portability and Accountability Act (HIPAA) [82]. This will then constrain the system designers as well

as imply other policies in the system such as assignment policies.

Going back to the original medical billing system example, it can be seen that there must be at least three distinct agents in the system. By examining the access control matrix, along with the role diagram, it can be inferred that the same agent cannot play the *Service Aggregator* role along with any other role, since the *Service Aggregator* role must have read access on the Patient Files resource, but no other role may have read access on that resource. This implies there must be at least two agents. It is also implied that the same agent cannot play the *Service Coster* role along with any other role, since the *Service Coster* role must have update access on the Accounting Database, but no other role may have update access on that resource. Thus the only roles in this system that may be played by the same agent are the *Ebiller* and *Printer* roles. This is because they have the same access privileges. This means that our system must have at least three agents. Now if a system designer tried to construct this system with less than three agents, they should be given an error, as this would not be a valid design. It can also be seen that this access control matrix implies the assignment policies disallowing the assignment of agents to other roles once they have been assigned to *Service Aggregator* or *Service Coster* roles and that these roles must be played alone. Thus the assignment function must take this into account or else the system design will be invalid.

An important point here is that the access control matrix, while it does allow the roles *Ebiller* and *Printer* to be played by the same agent, it does not force them to be played by the same agent. Thus a system designer may build a system that forces the same agent to play both roles, disallows the same agent from playing both roles, or allows any combination. Access control matrices add further restrictions to how the system may be designed—they represent policies of the system.

C.5.2 Information Flow Policies

Information flow policies restrict how data may flow from one role to another. In this paper, we use the notion of properties of data. This allows us to more easily abstract the data that we care about, which is not necessarily the actual data in the system, but may be just one property of that data. For example, we may allow the even/odd property of an integer to be seen by a role, but we do not want the actual integer value to be seen by the same role.

While access control policies restricted how agents interact with resources, information flow policies restrict how agents may interact with each other. Information flow policies also further restrict what data agents may store in resources. The concept of noninterference, which is used in information flow, was first introduced by Goguen and Meseguer [83]. Noninterference ensures that the value of one property does not influence the value of another property. This concept is important in information flow because, if two properties interfere, the flow of one will imply the flow of another.

In order to specify these types of policies, more information about the data is needed. In the medical billing system example, one might imagine that the Patient Files resource contains confidential patient information and we do not want the *Service Coster, Ebiller,* and *Printer* roles to have access to this confidential information. This implies that *Service Aggregator* role should not cause any of this information to flow directly to agents playing those roles or to resources for which those roles have read access (and of course, the role should not have access to a resource that is the source of the property).

The first thing that we need, then, is to identify the properties of the data for which we are interested in restricting access. Second, we need to create the policies that will restrict to what roles the properties may flow. In validating a system, we must identify the possible flows and verify that none of the flow policies are violated.

The first step of identifying the properties of the data creates the need to specify these properties. For the medical billing example, we might have the projected schema of the Patient Files resource as in Figure C.6. Now, the result of the tests performed should be

ID	Patient	Test	Date	Result
1	Smith	TB	10/5/06	Positive
2	Jones	ABC	11/2/06	Negative
3	Watson	Pre	11/5/06	Positive

Figure C.6: Patient Files resource projected schema.

ID	Patient	Test	Date	Cost
1	Smith	TB	10/5/06	
2	Jones	ABC	11/2/06	
3	Watson	Pre	11/5/06	

Figure C.7: Accounting Database resource projected schema.

kept secret from agents playing the other roles. This means that the other roles should not have access to this resource and that the role (*Service Aggregator*) that has access to this resource should not allow the information to flow to agents playing the other roles. The first part, no other role should have access to this resource, is enforced through access control policies. The second part, must be ensured by examining the protocols between the agents and the the resource access.

In the medical billing system example, the *Service Aggregator* role can read from the Patient Files resource and also can write to the Accounting Database resource. This means we have a flow between these two resources. Since the Accounting Database resource allows read access from other roles, we need to make sure that the flow between the resources does not leak any information that the roles accessing the Accounting Database are not allowed to acquire. In this example, the test results is a piece of information that should not flow between the two resources. Figure C.7 gives a projected schema of the Accounting Database resource.

Through an informal inspection, it can be seen that the result column cannot be transferred to the accounting database. It still must be verified, however, that the test result may not be inferred by the value of any other column. In this example, we simply assert that the other columns are not interfered by the contents of the result column. This means that the value of the data items are not influenced by the value of the result column. We also assert

that the agent playing the *Service Aggregator* role does not combine the result value with any other value that it inserts into the Accounting Database. With these assertions we can say that the value of the result column does not flow from the Patient Files resource to the Accounting Database resource.

The protocol analysis must insure that the result column does not interfere with any data sent to the other agent. In this example, the protocol will be a single message consisting of "price services" along with a list of IDs to process. This message indicates that the agent playing the *Service Aggregator* has inserted some data into the Accounting Database resource for the *Service Coster* to price. Thus, there is no flow of the result column over a direct channel. As for covert channels, we assert that there is no timing difference for the message based on the result column. Thus we may conclude, that the value of the result does not flow over a covert channel.

The policy, which states the result information should not be accessible to any role except the *Service Aggregator* role, forces the system designer to not store the test result in the Accounting Database. It also implies that the access control matrix may not give the other roles access to the Patient Database resource. For example, the system designer might want to give the *Printer* role access to the Patient files so that it might be able to print more information about the services rendered. However, since the *Printer* role would now have access to the result value, this system would be invalid and thus disallowed.

One may notice here that information flow policies may imply the specification of access control policies—whenever the property of the data being restricted is stored in a resource, there must be an access control policy to restrict access to that resource. Information flow policies may also imply the specification of assignment policies. In the medical billing system example, an agent cannot play the *Service Aggregator* role along with any other role because the result data cannot flow to an agent playing any of the other roles. These policies can be automatically generated by a security policy analysis tool. The generated policies must be checked against user defined to policies to verify that there are no conflicts. This automatic

$$
\begin{array}{c}
[\![r_x \ \mathbf{acc} \ \theta_y]\!] = \text{role } r_x \text{ accesses resource } \theta_y \\
[\![r_x \ \mathbf{use} \ p_y]\!] = \text{role } r_x \text{ uses protocol } p_y \\
[\![\theta_x \ \mathbf{cont} \ \upsilon_y]\!] = \text{resource } \theta_x \text{ contains property } \upsilon_y \\
[\![p_x \ \mathbf{trans} \ \upsilon_y]\!] = \text{protocol } p_x \text{ transmits property } \upsilon_y \\
[\![\upsilon_x \parallel \upsilon_y]\!] = \text{property } \upsilon_x \text{ is independent of property } \upsilon_y \\
[\![r_x \ \mathbf{acc} \ \upsilon_y]\!] = \exists \upsilon_y : \Upsilon, \exists r_x : \mathcal{R} \mid \\
[(\exists p_z : \mathcal{P} \mid r_x \ \mathbf{use} \ p_z \wedge p_z \ \mathbf{trans} \ \upsilon_y) \vee \\
(\exists \theta_z : \Theta \mid r_x \ \mathbf{acc} \ \theta_z \wedge \theta_z \ \mathbf{cont} \ \upsilon_y) \vee \\
(\exists \upsilon_z : \Upsilon \mid \neg(\upsilon_y \| \upsilon_z) \wedge r_x \ \mathbf{acc} \ \upsilon_z)]
\end{array}
$$

Figure C.8: Operator semantics.

generation of policies is described in more detail in Section C.8.

C.6 Security policy reasoning

Given the models defined above, we would like to formally reason about a specific design to make sure that it is a consistent and valid design. To this goal, we give a formalism, which allows us to reason about the design. The various components of the models may be described as follows: set of resources (Θ), set of roles ($\mathcal{R}$), set of agents ($\mathcal{A}$), set of protocols ($\mathcal{P}$), set of properties of data (Υ), and set of assertions (Ψ).

Figure C.8 gives the operators and their semantics. The **acc** operator denotes access capability. This operator is overloaded in that it may either denote access of a *property* or access of a *resource*. The **use** operator denotes use of a protocol. **cont** denotes that a *resource* contains a certain *property*. The **trans** operator denotes that a *protocol* transmits a certain *property*. Property independence is denoted using the $\parallel$ operator. By property independence, it is meant that the two properties do not influence each other in any way (the value of one property in no way affects the value of the other property).

The **acc**, **use**, **cont**, and **trans** operators are extended with the '*' suffix to indicate the entire set being denoted as given in Figure C.9. This is a natural and useful extension of the semantics defined in Figure C.8.

$$[\![r_x \textbf{ acc}^* \{\upsilon_y, \upsilon_z, ...\}]\!] = \text{role } r_x \text{ accesses only properties } \{\upsilon_y, \upsilon_z, ...\}$$
$$[\![r_x \textbf{ acc}^* \{\theta_y, \theta_z, ...\}]\!] = \text{role } r_x \text{ accesses only resources } \{\theta_y, \theta_z, ...\}$$
$$[\![r_x \textbf{ use}^* \{p_y, p_z, ...\}]\!] = \text{role } r_x \text{ uses only protocols } \{p_y, p_z, ...\}$$
$$[\![\theta_x \textbf{ cont}^* \{\upsilon_y, \upsilon_z, ...\}]\!] = \text{resource } \theta_x \text{ contains only properties } \{\upsilon_y, \upsilon_z, ...\}$$
$$[\![p_x \textbf{ trans}^* \{\upsilon_y, \upsilon_z, ...\}]\!] = \text{protocol } p_x \text{ transmits only properties } \{\upsilon_y, \upsilon_z, ...\}$$

Figure C.9: Extended operator semantics.

C.6.1 Reasoning example

In the patient billing system example described in the previous sections, let the role *Service Aggregator*, be r_1, *Service Coster*, r_2, *Printer*, r_3, and *Ebiller*, r_4. Let resource *Patient Files* be θ_1 and resource *Accounting Database*, θ_2. The protocols will be labeled as follows: *price services*, p_1; *print bill*, p_2; and *send bill*, p_3. For each property, we will simply use the data value of each field. Let *ID* be υ_1, *Patient* be υ_2, *Test* be υ_3, *Date* be υ_4, *Result* be υ_5, and *Cost* be υ_6.

From the models defined in the previous sections we may derive the following information:

$$\Theta = \{\theta_1, \theta_2\} \tag{C.1}$$
$$\mathcal{R} = \{r_1, r_2, r_3, r_4\} \tag{C.2}$$
$$\mathcal{A} = \{a_1, a_2, a_3, a_4\} \tag{C.3}$$
$$\mathcal{P} = \{p_1, p_2, p_3\} \tag{C.4}$$
$$\Upsilon = \{\upsilon_1, \upsilon_2, \upsilon_3, \upsilon_4, \upsilon_5, \upsilon_6\} \tag{C.5}$$
$$\Psi = \{\psi_1, \psi_2, \psi_3, \psi_4, \psi_5, \psi_6\} \tag{C.6}$$

Let us assert that all of the data in our billing system is independent, thus we have the fact:

$$\psi_1 = \upsilon_1 \| \upsilon_2 \| \upsilon_3 \| \upsilon_4 \| \upsilon_5 \| \upsilon_6 \tag{C.7}$$

From our role model in Figure C.2, we know that:

$$\psi_2 = \quad r_1 \textbf{ use } p_1 \wedge r_2 \textbf{ use } p_1 \wedge r_2 \textbf{ use } p_2 \ \wedge \tag{C.8}$$
$$r_3 \textbf{ use } p_2 \wedge r_2 \textbf{ use } p_3 \wedge r_4 \textbf{ use } p_4$$

$$\psi_3 = \quad r_1 \ \mathbf{acc}^* \ \{\theta_1, \theta_2\} \wedge r_2 \ \mathbf{acc}^* \ \{\theta_2\} \ \wedge \tag{C.9}$$
$$r_3 \ \mathbf{acc}^* \ \{\theta_2\} \wedge r_4 \ \mathbf{acc}^* \ \{\theta_2\}$$

Let us write the policy that property υ_5 should not be known (or flow) to roles r_2, r_3, and r_4:

$$\neg(r_2 \ \mathbf{acc} \ \upsilon_5 \vee r_3 \ \mathbf{acc} \ \upsilon_5 \vee r_4 \ \mathbf{acc} \ \upsilon_5) \tag{C.10}$$

Recall from the specification that property υ_5 is the test result. We are therefore specifying that we do not want the test result data to flow to the *Service Coster*, *Printer*, and *Ebiller* roles. Since we have that υ_5 is independent of all the other properties, ψ_1, and we have that roles, r_2, r_3, and r_4 only access resource θ_2, ψ_3, it will suffice to prove that:

$$\neg(\qquad p_1 \ \mathbf{trans} \ \upsilon_5 \vee p_2 \ \mathbf{trans} \ \upsilon_5 \vee \tag{C.11}$$
$$p_3 \ \mathbf{trans} \ \upsilon_5 \vee p_4 \ \mathbf{trans} \ \upsilon_5 \vee \theta_2 \ \mathbf{cont} \ \upsilon_5)$$

From the model, we know:

$$\psi_4 = p_1 \ \mathbf{trans}^* \ \{\upsilon_1\} \tag{C.12}$$
$$\psi_5 = \theta_2 \ \mathbf{cont}^* \ \{\upsilon_1, \upsilon_2, \upsilon_3, \upsilon_4, \upsilon_6\} \tag{C.13}$$
$$\psi_6 = \theta_1 \ \mathbf{cont}^* \ \{\upsilon_1, \upsilon_2, \upsilon_3, \upsilon_4, \upsilon_5\} \tag{C.14}$$

With ψ_4 we must only prove $\neg(p_2 \ \mathbf{trans} \ \upsilon_5 \vee p_3 \ \mathbf{trans} \ \upsilon_5 \vee p_4 \ \mathbf{trans} \ \upsilon_5 \vee \theta_2 \ \mathbf{cont} \ \upsilon_5)$. Let us assume that $\neg(r_2 \ \mathbf{acc} \ \upsilon_5 \vee r_3 \ \mathbf{acc} \ \upsilon_5 \vee r_4 \ \mathbf{acc} \ \upsilon_5)$. If this is true, then we have that $\neg(p_2 \ \mathbf{trans} \ \upsilon_5 \vee p_3 \ \mathbf{trans} \ \upsilon_5 \vee p_4 \ \mathbf{trans} \ \upsilon_5)$. With that information, we must only prove $\neg(\theta_2 \ \mathbf{cont} \ \upsilon_5)$. Since we know, ψ_5, we have $\neg(\theta_2 \ \mathbf{cont} \ \upsilon_5)$ and thus the policy holds.

We can also prove that a security policy is violated. For example, we might have the security policy that property υ_5 should not be known by role r_1:

$$\neg(r_1 \ \mathbf{acc} \ \upsilon_5) \tag{C.15}$$

This is clearly violated. Working toward a contradiction, let us assume Equation C.15. By using the definition of **acc** , then Equation C.16 must be true.

$$\neg\exists\theta_z : \Theta \mid r_1 \ \mathbf{acc} \ \theta_z \wedge \theta_z \ \mathbf{cont} \ \upsilon_5 \tag{C.16}$$

However, we know by ψ_6 that θ_1 **cont** υ_5 and by ψ_3 we know that r_1 **acc** θ_1, thus we have for $\theta_1 : \Theta$:

$$r_1 \textbf{ acc } \theta_1 \wedge \theta_1 \textbf{ cont } \upsilon_5 \tag{C.17}$$

With Equation C.16 and Equation C.17 we have a contradiction. Thus the policy in Equation C.15 is false and we can conclude that r_1 **acc** υ_5 .

Additional rules for these formalisms may be inferred. For example, we know that a policy cannot possibly transmit a property if it is never used by an agent who has access to this property. Thus we have for $p : \mathcal{P}, \upsilon : \Upsilon$:

$$\neg\exists r : \mathcal{R} \mid r \textbf{ use } p \wedge r \textbf{ acc } \upsilon \rightarrow \neg(p \textbf{ trans } \upsilon) \tag{C.18}$$

This is not an implication in both directions, because, even if an agent has access to a property, this does not mean that it will transmit this property over a protocol. These sort of rules can be useful in optimizing an algorithm that is designed to prove security properties of a system, since they could prune much of the proof space.

C.6.2 Automating Security Policy Reasoning

Reasoning over security policies by hand is tedious and error prone. Since we have tools to help the designer construct a multiagent system, it follows that we should provide tools to automate the reasoning and specification of security policies. This automation will allow the system designer to be able to test different security policies as well as assure that the given security policies are consistent with the rest of the specification of the system.

We constructed a tool that uses a SAT solver to answer questions and to verify security policies in a given multiagent system. The design of the software is broken into four parts as depicted in Figure C.10. The first part is the First Order Logic Abstract Syntax Tree (FOL AST). The FOL AST stores the atoms (agents, roles, goals, resources, properties, and protocols) as well as the relationships between those atoms using first order logic. The second part is the security expression builder. This part takes as input all the information from the various models as well as the security policies to construct a first order logic equation.

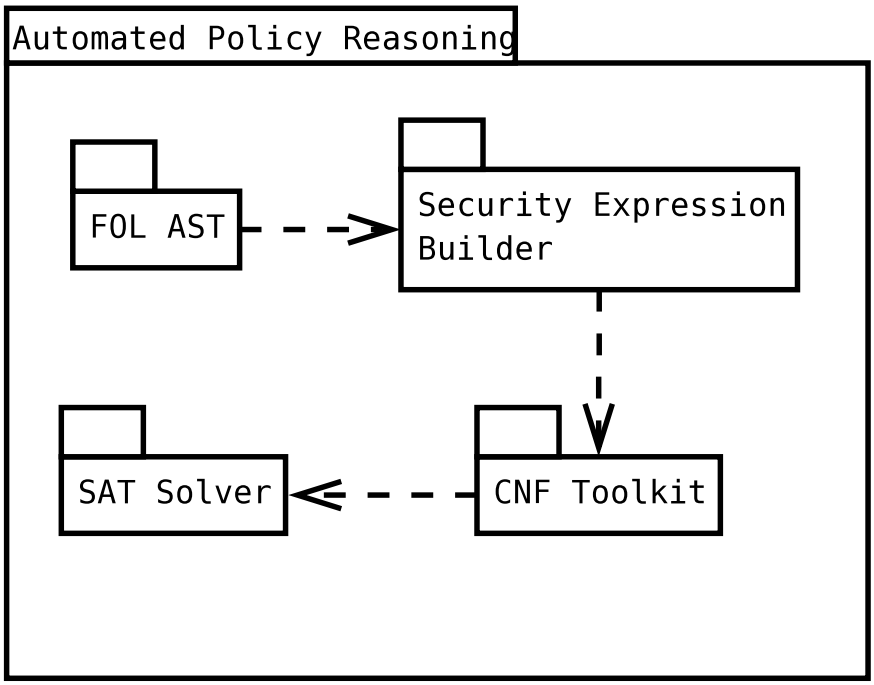

Figure C.10: Automatic policy verification system architecture.

The third part is the Conjunctive Normal Form (CNF) Toolkit. This part converts the general first order logic to CNF formalizations. The fourth part is the interface with the Satisfiability (SAT) Solver. This interface allows the application to use any SAT solver as well as output a standard CNF file to be solved in an external SAT solver such as zChaff [70].

The tool described above takes as input the various models given in this paper as well as the security policies to verify. The formulas given in Figure C.8 are combined with the facts derived from the various models. The policy is negated and added to the formulas. The quantification are unrolled and then the first order logic formulas are converted to CNF. If the SAT solver finds a satisfying assignment, the policy can be violated, and the assignment set it returns is a proof of violation. If the SAT solver does not find a satisfying assignment, the policy cannot be violated.

Figure C.11 shows the code involved in running the check on a security policy. In this case we are testing if role r_1 has access to property v_5. All the sets defined in the previous

```
Expression e = SecurityExpressionBuilder
        .generateSecurityExpression(roles, protocols,
                                    resources, properties,
                                    uses, accrs, conts,
                                    trans, relations);
e = new AndOp(e, AccLiteral.instanceOf(r1, pr5));
Expression f = CNFUtil.convertToCNF(e);
SATSolver solver = new SATSolver();
solver.isSatisfiable(new CNFFormula(f));
```

Figure C.11: Checking 'can r_1 access property v_5'.

section are used. The tool was executed on an Intel 2.13 GHZ processor with 1 GB of RAM running Slackware Linux. This particular query completed in 1.34 seconds and used less than 64 MB of RAM. The SAT solver we used for these tests was SAT4J [84] version 17rc2.

The violation (see Equation C.15) that we previously found by hand was found by the tool. The tool found the violation and then printed a satisfying assignment:

```
[r1 use p1] [r2 use p1] [r2 use p2]
[r3 use p2] [r2 use p3] [r4 use p4]
[r1 accR rs1] [r1 accR rs2] [r2 accR rs2]
[r3 accR rs2] [r4 accR rs2] [rs1 cont pr1]
[rs1 cont pr2] [rs1 cont pr3] [rs1 cont pr4]
[rs1 cont pr6] [rs2 cont pr1] [rs2 cont pr3]
...
```

These satisfying assignments can be quite large and much of the information may be irrelevant to the violation. Future work should be done to take care in presenting the violation in a way that allows the system designer more easily see the cause of the violation. However, simply being able to automatically check for the violations is a vast improvement.

An important fact to see here is that the *generateSecurityExpression* method makes the assumption that all relations are given and, if a relation is not in a given set, that the

negative relation is implied. For example, if it is not specified that a role uses a particular protocol, the tool makes the assumption that the role will not use that protocol. This is similar to the extended operator semantics given in Figure C.9.

We also tested the security policy specified in Equation C.10. The tool completed the query in 1.64 seconds and also used less than 64MB of RAM. It returned *Unsatisfiable*, which means that the policy cannot be violated with the given system design. This confirms the proof we made by hand earlier in the paper.

C.7 Conclusions

Multiagent software engineering has become an important paradigm for designing complex systems. As it is employed in more situations, the need for defining and proving security constraints becomes greater. Specifying security at the higher level of MAS has many benefits. The most common security concerns of a system are resource access and information flow.

We have defined a specification for these security constraints as applied to the O-MaSE. Through our example, it can be seen that this specification allows a group of designers to define and check security constraints. This is important because the ones making the security constraints are not necessarily the same ones who design the rest of the system. We also introduced a way to formally reason about these new models and give some example proofs.

While we have used O-MaSE and OMACS in this paper, these concepts should be able to be adapted to other multiagent system engineering methodologies. The reasoning, in particular, is fairly general since most multiagent systems will involve roles, agents, protocols, and properties.

Security has previously not been tightly integrated into a multiagent software engineering methodologies. The techniques and models described in this paper allow designers to specify and test security policies. Two of the basic security concerns have been demonstrated and

modeled. This approach gives designers a more complete integration of security into their design process than was previously possible in multiagent system engineering.

The reasoning given uses a modular approach. We use facts that may be obtained by analyzing parts of the model, such as the protocols, or the resource accesses. This sort of modularity allows for a more scalable reasoning. This is important as many multiagent systems can be quite large.

Security in multiagent systems will continue to be an important area of research, which will need to have more formalized constraints placed upon it. In this way, we will be able to prove that a multiagent system will behave reliably and have the desired security properties.

C.8 Limitations

Currently, we have only made a specification for access control and information flow policies. However, there are other security constraints that could be of interest. There are also questions to be answered about the impact of policies on the performance of the system.

For example, authentication is a huge part of security that is needed to ensure proper access control and information flow. There is also much that can be done to ensure that the implementation actually preserves the security properties ensured in the design models. The impact of various security policies on the flexibility of the system is also a possible area of research. This has been explored for different role models [35] and could be extended to policies.

Many assertions were used above to prove the data property flow policy given in Section C.6. Some of these assertions are assumptions, which could be later proved. The independence of properties is one example of such an assumption. This should be proved that, at least in the model, the properties do not influence each other. Then, in the implementation, it must be assured that they do not influence each other. The protocols also need to be shown to transmit only certain properties. An important thing to see here is that all this reasoning may be done in a modular fashion to allow for greater scalability.

As we previously demonstrated, the specification of some policies imply the specification of other policies. This can be automated by creating a system which fills in templates that are created for specific policy types much like the specification patterns described in [48]. These templates contain variables that will be filled in depending on what the security policy states. More work needs to be done in this area. In particular, generation of a sufficient number of templates to cover the common security policies, or general enough templates so that they can cover a large number of cases. For the cases not covered, policies would still have to be manually defined, but the system described here would still be able to detect if there was a violation.

The presentation of counter examples can also be improved. Currently, every boolean variable is displayed even if it is not relevant to the policy violation. Constructing a minimal relevant set would require further research and most likely involve scenario construction. The hope, however, is that the system would be able to guide the designer to create sufficient policies so that there would be less of a chance of a violation of a security policy. Also, the security policies can be incrementally checked as the design of the system evolves so that the designer could immediately see the impact of any design changes—specifically, design changes that cause security policies to be violated.

Work needs to be done to integrate both the specification and the verification into current state of the art multiagent system engineering tools such as agentTool III (aT3) [85]. Integration of security policy specification and verification into multiagent system design tools is the key to successfully incorporating security into multiagent systems.