DISSERTATION

Titel der Dissertation

The Quality-Aware Service Selection Problem: An Adaptive Evolutionary Approach

Application to the Selection of Distributed Data and Software Services in the ATLAS Experiment

Verfasserin

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I dedicate this thesis to my father, in loving and thankful memory.

Abstract

Quality of Service (QoS) is an important aspect in distributed, service-oriented systems. When several concrete services exist that implement the same functionality, the choice of a service instance among many can be made based on QoS considerations, objectives and constraints. Typically considered properties are performance, availability, and costs. When several services need to be composed in order to respond to a request, the resulting problem is more complex, as local QoS attributes have to be aggregated into global QoS values for the overall workflow, which is often spawned across organizational boundaries. To perform this aggregation, the specific attributes as well as the involved workflow patterns have to be known. Aiming for an *optimal* service selection can contribute to significantly reduce overall execution times, costs, or any other specifically formulated objective. The resulting challenge is referred to as the *QoS-aware service selection problem*.

In this thesis, aspects of the service selection problem are studied in the context of a distributed, service-oriented system from ATLAS, a high-energy physics experiment at CERN, the European Organization for Nuclear Research. In this so-called *TAG system*, data and modular services are distributed world-wide and need to be selected and composed on the fly, as a user starts a request. There are two conflicting optimization viewpoints, one of the user who wants requests to be executed as fast as possible, and one of the system managers seeking to load-balance between all available resources, thus optimizing the system throughput. The service selection is modeled as a dynamic multi-constrained optimal path problem, which allows considering both QoS attributes of service instances and of the network. The dynamic aspects of the system, such as removed or added resources, changing attributes and changing optimization objectives are included in the problem definition, as they represent a specific challenge.

To address these issues regarding dynamics and conflicting viewpoints, this work proposes a service selection optimization framework based on a multi-objective genetic algorithm capable of efficiently dealing with changing conditions by using a persistent memory of good solutions, and a stepwise adaptation of the mutation rate. A system and QoS attribute ontology as well as a description of dynamics of distributed systems build the basis of the framework. The presented approach is evaluated in terms of optimization quality (approximation of the Pareto front), adaptability to changes, runtime performance and scalability. Several parts of the overall optimization framework are ultimately integrated into the TAG system and evaluated therein. Although motivated by a concrete application, the framework is generally applicable to service selection challenges with specific characteristics close to the ones of the TAG system. A discussion about the operational effort of developing and maintaining such an optimization framework is provided and presents a guideline for the integration in further applications.

Kurzfassung

Die Qualität der Serviceerbringung (kurz QoS für "Quality of Service") ist ein wichtiger Aspekt in verteilten, Service-orientierten Systemen. Wenn mehrere Implementierungen einer Funktionalität koexistieren, kann die Wahl eines konkreten Services aufgrund von QoS-Aspekten getroffen werden. Leistung, Verfügbarkeit und Kosten sind Beispiele für QoS-Attribute eines Services. Wenn mehrere Services benötigt werden, um einen Workflow zu bilden, müssen lokale QoS-Attribute zu globalen Workflow-Attributen aggregiert werden, wobei der resultierende Workflow Services von verschiedenen Organisationen umfassen kann. Für eine solche Aggregation müssen sowohl die Attribute als auch die Workflowstrukturen bekannt und dokumentiert sein. Eine *optimale* Selektion von verteilten Services ist erstrebenswert, um zum Beispiel die gesamte Ausführungsdauer, entstehende Kosten oder sonstige definierte Ziele zu optimieren. Das resultierende Problem wird *"QoS-aware Service Selection Problem"* genannt.

In der vorliegenden Dissertation werden Aspekte dieses Selektionsproblems anhand eines konkreten, Service-orientieren Systems vertieft. Es handelt sich dabei um das *TAG-System* in ATLAS, einem Hochenergiephysikexperiment am CERN, der Europäischen Organisation für Kernforschung. Die Daten und Services des TAG-Systems sind weltweit verteilt und müssen auf Anfrage selektiert und zu einem Workflow zusammengesetzt werden. Die Optimierung wird aus zwei unterschiedlichen Blickwinkeln durchgeführt: dem eines Benutzers, der seine Anfrage so schnell wie möglich beantwortet haben möchte, und dem der Systemmanager, deren Ziel es ist, die Last auf alle zur Verfügung stehenden Ressourcen zu verteilen und somit den Durchsatz des Systems zu optimieren. Die Selektion wird als ein dynamisches Pfadoptimierungsproblem unter Nebenbedingungen modelliert, wodurch QoS-Attribute sowohl der Knoten (Services) als auch der Kanten (Netzwerk) berücksichtigt werden können. Die dynamischen Aspekte (z.B. wechselnde Ressourcen, Attribute, Optimierungsfunktionen oder Gewichte) sind in der Problemformulierung integriert, da sie eine spezifische Herausforderung und Anforderung an Lösungsalgorithmen stellen.

Für die dynamische Pareto-Optimierung von Serviceselektionsproblemen wird im Rahmen dieser Arbeit ein Optimierungsansatz mit einem genetischen Algorithmus präsentiert, der über einen persistenten Speicher von früheren Lösungen sowie eine automatische Adaptierung der Mutationsrate eine effiziente Anpassung an das sich ständig verändernde System gewährleistet. Eine Ontologie der Systemkomponenten sowie deren QoS-Attribute bildet die Basis für die Optimierung. Der Ansatz wird im Rahmen der Dissertation hinsichtlich der Qualität der erzielten Lösungen, der Adaptierung an Änderungen sowie der Laufzeit evaluiert. Teile des Ansatzes wurden schließlich in das TAG-System integriert und darin evaluiert. Obwohl der Ansatz im Rahmen eines spezifischen Serviceselektionsproblems entwickelt wurde, ist er in anderen Szenarien oder Systemen mit ähnlichen Charakeristika einsetzbar. Die Herausforderungen während der Entwicklung und des Betriebes des Optimierungsframeworks werden beschrieben und bilden somit eine Anleitung für dessen mögliche Integration in andere Systeme.

Acknowledgements

First and foremost, I would like to thank my adviser, Prof. Erich Schikuta. He has provided me with excellent guidance through my studies, carefully showing the way to a successful completion as a balance of curiosity, enthusiasm, and pragmatism. I also particularly thank David Malon from the Argonne National Laboratory for accepting to review my thesis, and for providing such a motivating work environment in the ATLAS TAG group.

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I am particularly thankful to Peter Paul Beran for numerous fruitful discussions and for being such a great co-author. Our cross-motivation in the last year has been crucial for completion. Further, I would like to thank Armin Nairz for his very detailed proof-reading and in general for the great “TAG - Tier-0” cooperation.

I am grateful to my friends here in Geneva, Austria and elsewhere, for their (remote) support and the great moments we shared, even if we had little time together in the past three years.

Friedrich, thank you for your encouragement and patience, and for “keeping me in balance,” by opening my eyes (and ears!) to exciting new things, and enriching my life in so many ways.

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Chapter 1

Introduction

In distributed, service-oriented systems, an abstract functionality – or *Service* – often exists in several concrete instances, implementations or *Deployments* only differing in non-functional attributes such as performance, availability, and reliability. When mapping an abstract service chain to a concrete one in response to a request, there are thus several options for substituting each service with a deployment. This choice influences the behavior of the concrete workflow in terms of *Quality of Service*. It is thus required to not randomly select deployments, but base the choice on considerations regarding QoS requirements, objectives and constraints. The resulting challenge is commonly referred to as the *QoS-aware Service Selection Problem*. This problem has recently been studied intensively, and many different approaches exist. They all aim at allowing some optimization, depending on the system requirements. Minimize the execution time of jobs, minimize costs associated with a task, maximize the overall throughput, and maximize some custom-defined utility function are example objectives for such an optimization.

This thesis is motivated by a concrete service selection challenge arising in the *TAG System*, a distributed, service-oriented system in the context of ATLAS [10], a High-Energy Physics (HEP) experiment at the Large Hadron Collider (LHC) [24, 26]. In the TAG system, services need to be selected and composed to form scientific workflows allowing an efficient preselection of ATLAS data. The service selection optimization is approached from two different, usually conflicting, angles, namely the user and the system provider perspectives. It is thus a multi-objective optimization problem. Additionally, the system is highly dynamic in several aspects. To address these issues, an adaptive and dynamic framework for the selection of services is proposed and its applicability is shown and evaluated in the ATLAS TAG system. The broader vision is to propose a global approach to QoS-aware service selection problems applicable to scenarios of various characteristics and sizes.

This introductory chapter is organized as follows. In Section 1.1 the *QoS-aware Service Selection Problem* is outlined and defined. Section 1.2 presents the motivation and research questions underlying this thesis. Section 1.3 outlines the challenges and main contributions of this work. Finally, Section 1.4 presents the structure of the thesis.

1.1 The QoS-Aware Service Selection Problem

A *Service* is a software component described by functional and non-functional attributes. The functional attributes, as the name suggests, describe the functionality a service exposes to the users, be they humans or other software components. This generally encompasses inputs, behavior, and outputs. These attributes thus describe *what* a service is doing. Non-functional attributes describe *how* a service accomplishes its functionality, i.e., they refer to characteristics related to the operations of services. Examples of non-functional attributes include performance, costs, reliability and availability. They are often referred to as Quality of Service (QoS) attributes. Although in literature the terms "non-functional attribute" and "QoS attribute" are often used likewise, in this work *QoS attributes* are defined as a subclass of *non-functional attributes*. For example, service configuration issues can be considered as non-functional attributes, but not directly related to a quality of service measure. In the remainder of this work, the term *non-functional attributes* is thus used when referring to the superclass, and the term *QoS attributes* is used when referring to the subclass.

Several abstract services can be composed to form an *abstract workflow*. When each service is substituted with a concrete deployment, the abstract workflow is mapped to a *concrete workflow*. Figure 1.1 shows three views of a simple sequential workflow. The user wants to perform four tasks (*select a set of data*, *define a query*, *count the resulting events* and *extract data*), for which five abstract services are needed. The service selection optimization process transforms the abstract service workflow into a concrete deployment workflow. Mathematically, this is commonly modeled as a multi-dimension multi-choice knapsack problem (MMKP). In an MMKP, a knapsack has to be filled with items that are classified into mutually exclusive object groups, each containing several different objects. The knapsack itself has a set of constraints. The objective of the MMKP is to pick exactly one item from each class in such a way as to maximize the total profit of the collected objects, subject to resource constraints of the knapsack [42]. In the same way, the QoS-aware service selection problem is to pick one deployment for each abstract service to build the concrete workflow, meeting defined QoS constraints and maximizing a total utility value (see Figure 1.2). The QoS-aware service selection problem can be mapped to an MMKP as defined by Yu et. al. [104]:

- Each abstract service is mapped to an object group.
- Each deployment of a service is mapped to an object in an object group.
- QoS attributes of deployments are mapped to resources of an object.
- The utility of a deployment is mapped to the profit of an object.
- QoS constraints are mapped to the resources available in the knapsack.

Let there be n abstract services, and l_i deployments for service i. Each deployment has m QoS attributes and a utility value c_{ij} (utility of the j^{th} deployment for service i). $\vec{q_{ij}} = (q_{ij1}, \ldots, q_{ijm})$ is the QoS vector for the j^{th} deployment for service i, and $\vec{Q} = (Q_1, \ldots, Q_m)$ is the QoS bound of the knapsack. x_{ij} are the picking variables. The MMKP can then be formulated as follows:

$$\begin{aligned}
\max \quad & \sum_{i=1}^{n}\sum_{j=1}^{l_i} c_{ij}x_{ij} \text{ (objective function)} \qquad (1.1)\\
\text{subject to} \quad & \sum_{i=1}^{n}\sum_{j=1}^{l_i} (q_{ij})_k x_{ij} \leq Q_k, k = 1, 2, \ldots, m \text{ (QoS constraints)}\\
& \sum_{j=1}^{l_i} x_{ij} = 1, i = 1, 2, \ldots, n\\
& x_{ij} \in 0, 1, \forall i, j
\end{aligned}$$

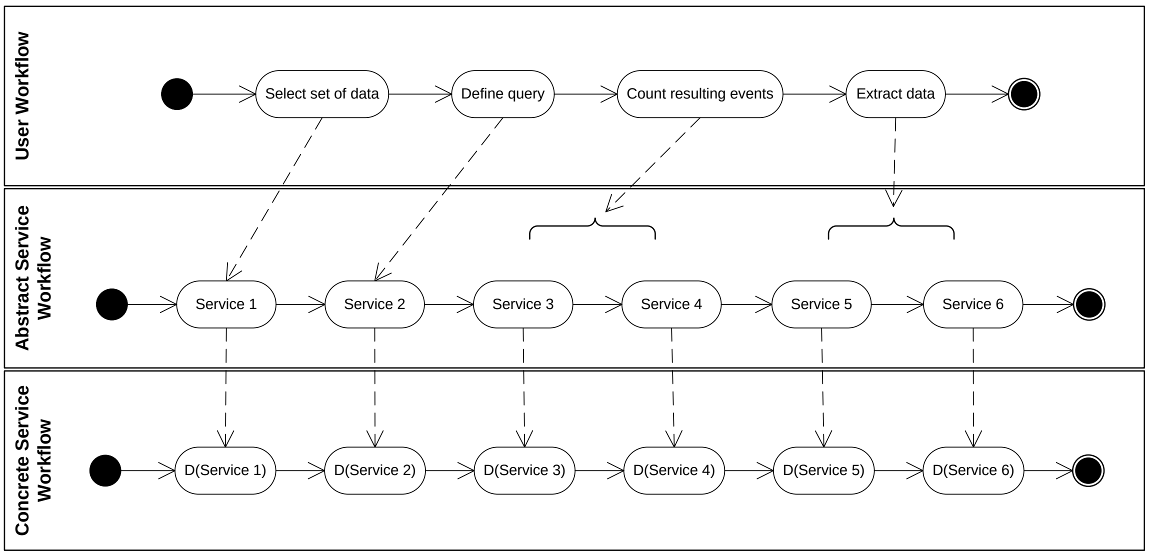


Figure 1.1: Mapping of Abstract to Concrete Workflow

This model does not take into account links between the services. Links cannot be considered as separate items or object groups, because of their dependencies to services. If one service is changed, then the incoming and outgoing links automatically change as well. Therefore, while conceptually being a knapsack problem ("take one item out of each group"), the service selection problem taking into account the links between services cannot be represented in the form of Equation 1.1. This is why the second common approach found in literature is to establish a graph-based model of the QoS-aware service selection problem [104]. This is referred to as the Multi-Constrained Optimal Path Problem (MCOP). An MCOP is defined as follows [58]:

Let $G = (V, E)$ be a directed graph, where V is the set of vertexes and E the set of edges of the graph. Each edge $(i, j) \in E$ has an associated non-negative cost parameter $c(i, j)$ and K additive non-negative QoS parameters $w_k(i, j), k = 1, 2, ..., K$. Given K constraints $c_k, k = 1, 2, ..., K$, the problem is to find a path p such that:

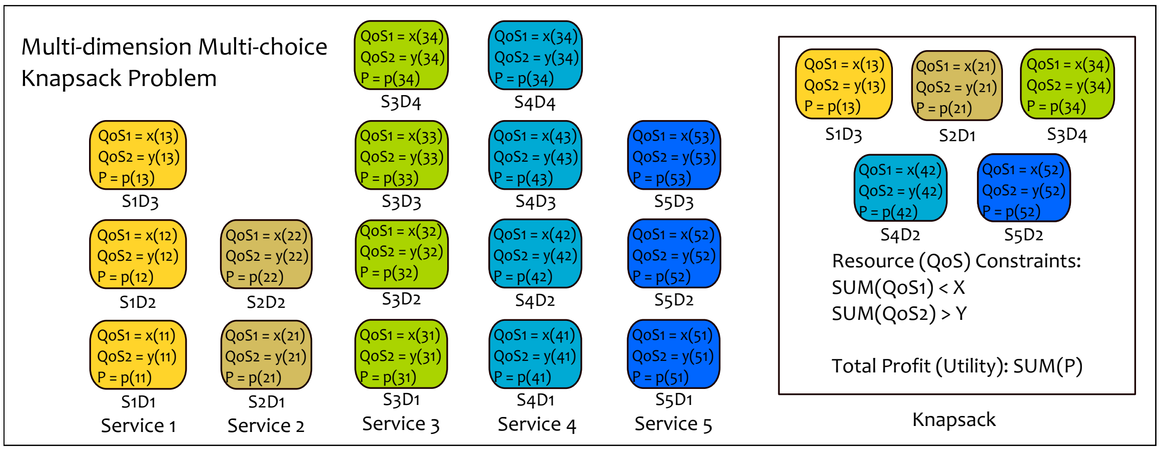

Multi-dimension Multi-choice Knapsack Problem
QoS1 = x(34) QoS2 = y(34) P = p(34) S3D4
QoS1 = x(34) QoS2 = y(34) P = p(34) S4D4
QoS1 = x(13) QoS2 = y(13) P = p(13) S1D3
QoS1 = x(33) QoS2 = y(33) P = p(33) S3D3
QoS1 = x(43) QoS2 = y(43) P = p(43) S4D3
QoS1 = x(53) QoS2 = y(53) P = p(53) S5D3
QoS1 = x(12) QoS2 = y(12) P = p(12) S1D2
QoS1 = x(22) QoS2 = y(22) P = p(22) S2D2
QoS1 = x(32) QoS2 = y(32) P = p(32) S3D2
QoS1 = x(42) QoS2 = y(42) P = p(42) S4D2
QoS1 = x(52) QoS2 = y(52) P = p(52) S5D2
QoS1 = x(11) QoS2 = y(11) P = p(11) S1D1
QoS1 = x(21) QoS2 = y(21) P = p(21) S2D1
QoS1 = x(31) QoS2 = y(31) P = p(31) S3D1
QoS1 = x(41) QoS2 = y(41) P = p(41) S4D1
QoS1 = x(51) QoS2 = y(51) P = p(51) S5D1
Service 1
Service 2
Service 3
Service 4
Service 5
QoS1 = x(13) QoS2 = y(13) P = p(13) S1D3
QoS1 = x(21) QoS2 = y(21) P = p(21) S2D1
QoS1 = x(34) QoS2 = y(34) P = p(34) S3D4
QoS1 = x(42) QoS2 = y(42) P = p(42) S4D2
QoS1 = x(52) QoS2 = y(52) P = p(52) S5D2
Resource (QoS) Constraints:
SUM(QoS1) < X
SUM(QoS2) > Y
Total Profit (Utility): SUM(P)
Knapsack

Figure 1.2: Multi-Dimension Multi-Choice Knapsack Problem

$$
\begin{aligned}
\min \quad & c_p = \sum_{(i,j)\in p} c(i,j) \text{ (objective function)} \\
\text{subject to} \quad & w_k = \sum_{(i,j)\in p} w_k(i,j) \leq c_k \text{ for } k = 1,...,K \text{ (QoS constraints)}
\end{aligned}
\tag{1.2}
$$

MMKPs as well as MCOPs are NP-hard, which means that most likely there are no polynomial-time algorithms to solve them [58, 71]. In modern, service-oriented systems, the problem space, i.e., the number of abstract services and concrete deployments, can be big enough for exact algorithms not to perform in acceptable time. Many heuristic approaches have thus been proposed for solving QoS-aware service selection problems, as presented in Chapter 3.

1.2 Motivation for a Dynamic and Adaptive Service Selection Optimization Framework

The motivation and application scenario of this thesis is the so called TAG System of the ATLAS experiment at CERN, the European Organization for Nuclear Research. The TAG system (described in detail in Chapter 2) supports metadata-based queries on data recorded at the ATLAS detector, in order to allow a quick preselection of relevant data to consider for further physics analysis. It supports a set of well-defined use cases through distributed Web and Grid services, using distributed data sources. The ATLAS Computing Model [9] defines a Tier structure, in which various sites around the world host data and services. Several deployments exist for each abstract service from the TAG system, each having the same implementation and version, but varying non-functional attributes depending on the site and resource they run on. When a user starts a request, a concrete process has to be instantiated, selecting one deployment per abstract service needed to deliver the functionality related to the request.

The TAG system has the following characteristics relevant to properly address the service selection challenge:

- **Central control:** although the data and services are distributed, there is a central instance at CERN that has knowledge about all services and can monitor them. This allows gathering statistics by aggregating logging information, and the status of the deployments is known at any time.

- **Tightly coupled components:** the individual abstract services are designed to work together. There are thus no compatibility issues in service composition.

- **Dynamic environment:** as in distributed systems in general, resources can be temporarily unavailable or decommissioned, new resources can be deployed, and attributes change over time. The system is thus dynamic, and a given system state is only valid for a certain period in time.

- **Known problem size:** although the system is dynamic, it is changing in a controlled way, and the problem size is known. For example, there will not be a sudden increase in the number of deployments by an order of magnitude.

- **Changing objectives:** in an application of a long-lasting scientific experiment like ATLAS, optimization objectives and/or their weights can change periodically. For example, in periods with low system usage, a single request can be optimized, whereas in periods of high system usage it is preferable to ensure a fair usage and request distribution. This requires the ability to monitor system activity and derive usage profiles.

- **Changing priorities:** in the TAG system as in other real-world application scenarios, it can be a requirement to prioritize some use cases over others in a defined time frame. For example, in a period of high data analysis activity (e.g., before conferences), single and composed services supporting efficient data extraction can be given priority over other use cases.

In many service selection studies (e.g., [3, 56, 105]), the optimization problem is addressed from the user's perspective only. A single user requests a certain functionality (e.g., video compression as in [56]), which requires several services to be selected and composed. The selection of deployments is done such that a user-defined utility function is optimized. For example, the response time can be minimized, while having constraints on the costs, or a utility function aggregating several QoS measures can be maximized. In any case, the optimization is carried out from the user's perspective, without taking into account the impact of the selection on other users. In the approach adopted in this work, however, two optimization perspectives are taken into account, the user's and the system provider's perspective. The goal is not only to maximize the utility of a single process, but also to optimize the system throughput, and to ensure a fair and efficient usage of the resources. The overall requirements and challenges of the TAG system are highlighted in Table 1.1.

To summarize, the overall problem can be formulated as follows. How can deployments be selected and composed in the TAG system, such that

- for each individual user, the overall response time is minimized,

- while, from a system perspective, ensuring a fair and efficient usage of all available resources,

- objectives and priorities can be set dynamically and

Perspective	Requirements
User	Transparent data and services distribution. Minimal execution time for each request. Reliable system with maximal availability.
System Provider	Use all resources and services efficiently. Allow fail-over mechanisms for TAG resources and services. Maximize the system's throughput.
Planning (Management)	Adapt to changing objective functions. Adapt to changing environment. Potentially, allow monitoring system capacity limitations.

Table 1.1: TAG System Requirements

- system changes are taken into account,
- while keeping the selection process efficient and without considerable impact on the overall performance?

The optimization process itself thus has to be *adaptive* to changing situations in terms of optimization requirements, and the underlying algorithm has to be able to react to *dynamics* of the system, i.e., changing conditions. A stand-alone algorithm, running each time a request is made, is thus not a sufficient solution. Based on the characteristics and requirements stated above, this thesis introduces an adaptive and dynamic QoS-aware service selection approach, and applies it to concrete scientific workflows. Although the described motivation and application environment is very specific, the proposed solution is generic and can be adapted to different scenarios.

1.3 Challenges and Contributions

Several building blocks had to be investigated to realize the presented service selection approach, each representing a contribution to the research topic. Figure 1.3 summarizes the issues that need to be addressed to realize service selection and composition. The main contributions of this thesis reside in system description (1) and algorithmic approach (4). They are addressed in Chapters 4 to 7. Service discovery (2) and workflow mapping (3) are briefly addressed from an implementation point of view in Chapter 4. In more detail, the contributions are the following:

Building a model of distributed systems, their components and attributes. In order to implement a service selection optimization framework into an existing distributed system, this system first has to be analyzed and described in detail. This analysis consists of the identification of the system components and attributes, and their interactions. To address this challenge, a system ontology and an attribute ontology have been developed. They are generic and meant to provide a high-level common language for the description of heterogeneous, distributed, service-oriented systems. These ontologies and the derived formal system description build the basis for the optimization framework. This contribution is presented in Chapter 4.

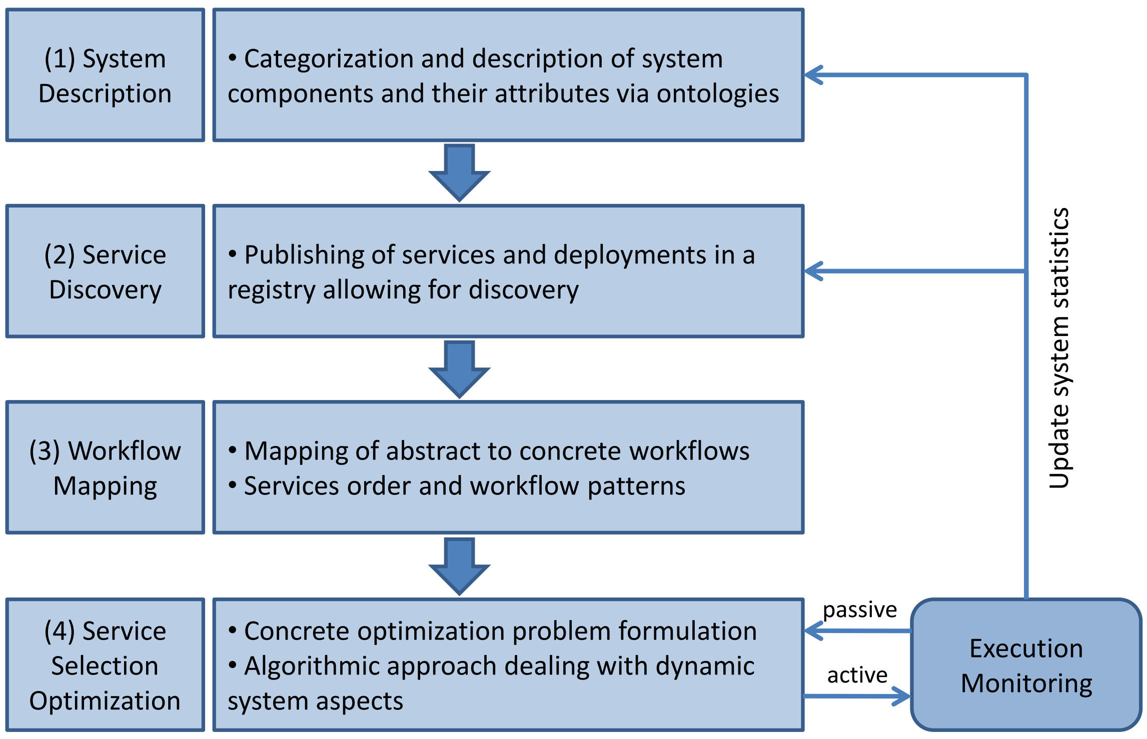

(1) System Description
• Categorization and description of system components and their attributes via ontologies
(2) Service Discovery
• Publishing of services and deployments in a registry allowing for discovery
(3) Workflow Mapping
• Mapping of abstract to concrete workflows
• Services order and workflow patterns
(4) Service Selection Optimization
• Concrete optimization problem formulation
• Algorithmic approach dealing with dynamic system aspects
passive
active
Execution Monitoring
Update system statistics

Figure 1.3: Challenges Addressed in the Thesis

Modeling dynamic aspects of QoS-aware optimization problems. As put forward in the previous section, the TAG system is dynamic in several aspects. In order to take this into account in the optimization problem formulation and in the algorithmic approach, these dynamic aspects have to be analyzed. Several questions arise: how can dynamic aspects be represented? How can they be detected? How can they be taken into account in the optimization process? To address these questions, a system representation through time-dependent profiles is proposed and the profiles are considered in the concrete problem formulation. This contribution is presented in Chapter 5.

Design and implementation of a genetic algorithm reflecting dynamics and adaptivity to changes. An **A**daptive and **D**ynamic **M**ulti-**O**bjective **G**enetic **A**lgorithm (AD-MOGA) is proposed for addressing all requirements of the service selection optimization in the TAG system. AD-MOGA is designed to be able to detect system changes and react to them. It is implementing a persistent memory and self-adapting mutation rate allowing the adaptation to changes in the optimization environment. AD-MOGA is presented in Chapter 6 and the results of its evaluation are discussed in Chapter 7.

Practical considerations for implementing a service selection optimization framework. Implementing a service selection optimization framework in a real-world system requires a logging, monitoring, implementation and maintenance effort. Based on the experience from the TAG system acquired in the context of this thesis work, an assessment of the operational effort and the achieved gains is provided, serving as guideline for the integration of the framework into other systems. This contribution is presented at the end of Chapter 7.

1.4 Thesis Structure

The thesis is structured in chapters as follows.

Chapter 2: Motivation and Application Scenario: TAG-based Metadata Queries in the ATLAS Experiment. This chapter presents the motivational environment that led to the research questions and that has been used as application domain. The thesis work has been carried out at CERN in the context of the TAG system, a distributed metadata system of the ATLAS experiment. The questions addressed in this chapter include:

- What is the TAG system and what is its role in the ATLAS experiment?
- What are the main TAG services that need to be selected and composed to respond to a request?
- Which aspects of the ATLAS TAG system motivated the research questions addressed in this thesis?

Chapter 3: Background and Related Work: Service Selection in Heterogeneous Environments. In this chapter, related work in the area of service selection in distributed, heterogeneous environments is discussed, leading to a state of the art study. The questions addressed in this chapter include:

- Which research areas are comparable to the QoS-aware service selection problem? What are the similarities and differences?
- How have distributed systems been modeled in previous work?
- How has the QoS-aware service selection problem been approached in previous work?

Chapter 4: An Ontology of Components and Attributes of Distributed, Service-Oriented Systems. In order to apply service selection optimization techniques to a system, this system and its characteristics and behavior first have to be understood and described. To do so, ontologies can be applied. This chapter presents a generic system and attribute ontology and a concrete derived model of the TAG system. The questions addressed in this chapter include:

- How can distributed systems in general and the TAG system in particular be modeled in order to identify all components that need to be included in a service selection optimization process?
- What are QoS attributes, how can they be gathered, classified and represented?
- Which design choices have been made for the *TAG Application Service Knowledge Base* and how is it implemented?

Chapter 5: QoS-Aware Service Selection: A Dynamic Multi-Objective Optimization Problem. Distributed, heterogeneous systems are usually highly dynamic. When selecting services, the underlying system thus has to be considered as constantly changing. In this chapter, the dynamic aspects are defined in detail, and the concrete optimization objectives for the TAG system, taking into account the dynamics, are derived. The questions addressed in this chapter include:

- What are dynamic aspects of distributed systems in general and the TAG system in particular, and how can they be represented in system profiles?
- What are the exact optimization objectives being studied in the context of the TAG system?
- How can multi-objective optimization in dynamic environments be addressed?

Chapter 6: Designing Genetic Algorithms for Service Selection Optimization Problems. Genetic Algorithms (GA) can be used to solve dynamic multi-objective optimization problems, and different concrete techniques can be applied to capture the dynamic aspects. This chapter investigates those approaches and presents an adaptive and dynamic multi-objective genetic algorithm (AD-MOGA) tailored to service selection problems. The questions addressed in this chapter include:

- Why and how can genetic algorithms be used for multi-objective optimization in dynamic environments?
- What are the design considerations for dynamic genetic algorithms applied to service selection problems?
- What are the characteristics of the proposed algorithm, AD-MOGA?

Chapter 7: Implementation and Evaluation. In this chapter the AD-MOGA approach is evaluated regarding several relevant criteria such as quality, runtime and adaptability to changes. Further, the integration of the proposed service selection optimization framework into the TAG service selection is described. The questions addressed in this chapter include:

- How well does AD-MOGA approximate the Pareto solutions in simulated service selection problem scenarios?
- How does AD-MOGA adapt to changes in the underlying system, and what are the resulting advantages?
- What are the performance benchmarks of AD-MOGA in terms of runtime and scalability?
- What are the main operational challenges in designing, implementing and maintaining the presented optimization framework?
- What are the arising future research directions?

Chapter 8: Conclusion. This chapter summarizes and concludes the thesis.

Chapters 4, 5, 6 and 7 are partly derived from the following publications:

- E. Vinek, P.P. Beran and E. Schikuta. Mapping Distributed Heterogeneous Systems to a Common Language by Applying Ontologies. In *Proceedings of the* 10th *IASTED International Conference on Parallel and Distributed Computing and Networks*, Innsbruck, Austria, 2010. [88]
- E. Vinek and F. Viegas. Composing Distributed Services for Selection and Retrieval of Event Data in the ATLAS Experiment. In *Conference on Computing in High Energy and Nuclear Physics (CHEP)*, Taipei, Taiwan, October 2010. [89]
- E. Vinek, P.P. Beran and E. Schikuta. Classification and Composition of QoS Attributes in Distributed, Heterogeneous Systems. In 11th *IEEE/ACM International Symposium of Cluster, Cloud and Grid Computing (CCGrid)*, Newport Beach, USA, 2011. [86]
- E. Vinek, P.P. Beran and E. Schikuta. A Dynamic Multi-Objective Optimization Framework for Selecting Distributed Deployments in a Heterogeneous Environment. In *The International Conference on Computational Science (ICCS)*, Singapore, 2011. [85]
- E. Vinek, P.P. Beran and E. Schikuta. Comparative Study of Genetic and Blackboard Algorithms for Solving QoS-Aware Service Selection Problems. Poster at *The 2011 International Conference on High Performance Computing & Simulation (HPCS 2011)*, Istanbul, Turkey, 2011. [87]
- P.P. Beran, E. Vinek and E. Schikuta. A Distributed Database and Deployment Optimization Framework in the Cloud. Accepted as short paper at *The* 13th *International Conference on Information Integration and Web-based Applications & Services (iiWAS2011)*, Ho Chi Minh City, Vietnam, December 2011. [13]

Most of these publications have been done together with Peter Paul Beran, who is currently working on a blackboard-based approach for the optimization of distributed database queries. While the motivation and key contributions from the two approaches are different, some ideas have been developed and implemented together, in joint work. This applies specifically to the following parts:

- Categorization of components and attributes of distributed, service-oriented systems (Chapter 4): the main classes and attributes have been identified, classified and published together. The development of the ontology itself, its implementation using a specific toolkit, and the application of the ontology to the TAG system have however been carried out by the author herself and are thus contributions specific to this thesis.
- Quantifying system changes (Chapter 5, Section 5.2.3): the main ideas of this section have been developed together.
- Service selection strategies: general service selection strategies have been discussed together, and applied to a common simulation environment. The genetic algorithm presented in Chapter 6 has been developed by the author herself and is a contribution of this thesis only. P.P. Beran uses a blackboard with an A^* algorithm for a similar problem and his particular application scenario. The implementation and evaluation environment (Chapter 7) in its original form has been developed together and has then been customized by each author for his/her particular needs.

The differences in the optimization approaches can be explained by the differing characteristics of the application scenarios. While the TAG system is centrally controlled, has tightly coupled components and a known problem size, the scenario studied in P.P. Beran's work has no central control instance, loosely coupled components and in general incomplete knowledge about the system components and their attributes. Different approaches are thus required to deal with those issues. Additionally, P.P. Beran focuses specifically on the optimal combination of distributed database operators. Despite those differences, the two works can be regarded as complementary, because each investigates specific aspects and application scenarios of a similar problem.

Chapter 2

Motivation and Application Scenario: TAG-based Metadata Queries in the ATLAS Experiment

This chapter presents the thesis environment that serves as motivation as well as application and evaluation domain. The presented work has been performed at CERN, the European Organization for Nuclear Research, located on the outskirts of Geneva, at the border between Switzerland and France. CERN hosts the Large Hadron Collider (LHC), currently the world's largest and most powerful particle accelerator [24]. The LHC is made up of a ring of superconducting magnets, in which two beams travel with high energy in opposite directions inside dedicated beam pipes, before finally colliding. Collisions are recorded within detectors that reside along the 27 km long LHC ring. ATLAS (A Toroidal LHC ApparatuS) is one of the HEP experiments at the LHC [26]. This thesis work has been carried out in the context of the ATLAS TAG system. This system is composed of data sources that host metadata describing the Events (i.e., particle collision instances) recorded at the ATLAS detector, and services needed to access and process this data.

For studying the service selection problem in general, it it not necessary to know the specific functionality of services – it can be treated in a generalized, abstract way. However, as our approach is motivated by and applied to a specific system, it is useful to describe the nature and scope of the services in question in more detail. This chapter also serves as a general description of the current status of the TAG system.

The organization of this chapter is as follows. Section 2.1 gives a brief overview of the ATLAS experiment. In Section 2.2 the standard data reconstruction process, from RAW data recorded at the detector to the production of metadata, is described. Section 2.3 lists and briefly outlines the main TAG services. A typical TAG workflow is described in Section 2.4. Finally, Section 2.5 describes the data and services distribution and outlines the thesis challenge arising from this distribution.

2.1 The ATLAS Experiment at the LHC

ATLAS [10] is one of the particle detectors ("experiments") at the LHC. It is a multi-purpose detector designed to investigate a large range of physics, including the search for dark matter, new physics like supersymmetry or extra dimensions, and the origin of mass. The latter involves the search for the so-called Higgs boson, a missing piece in the Standard Model that would explain how particles gain mass. The detector has several subsystems, each detecting specific types of particles and determining their momentum and energy [7]. Figure 2.1 shows a computer-generated view of the ATLAS detector, with its subsystems and dimensions.

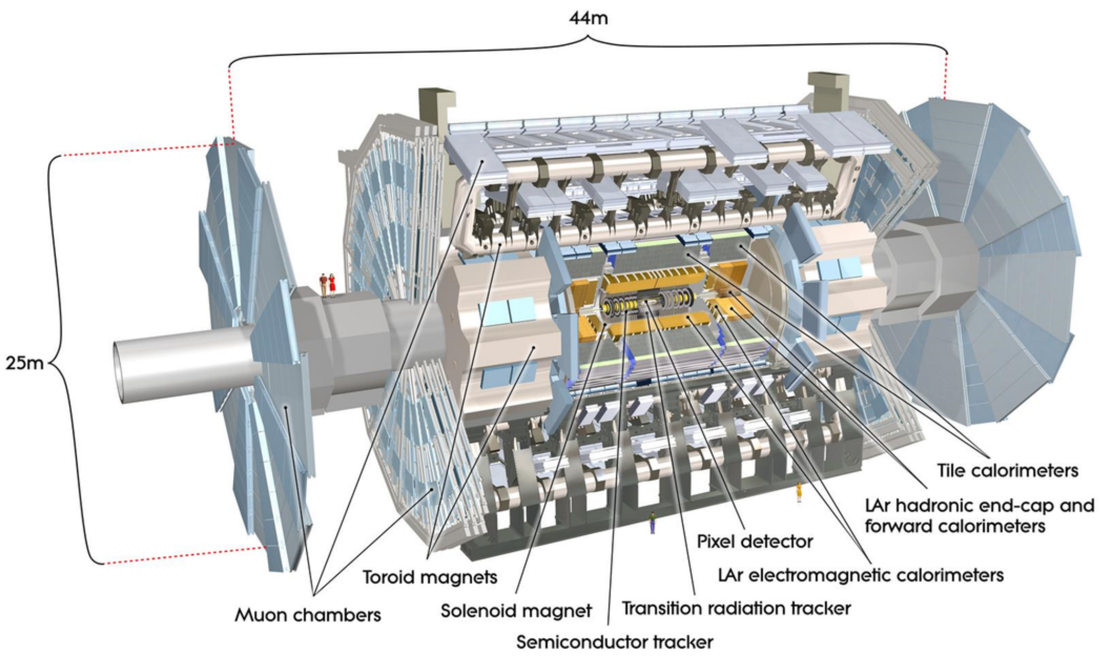

44m
25m
Tile calorimeters
LAr hadronic end-cap and forward calorimeters
Pixel detector
LAr electromagnetic calorimeters
Toroid magnets
Muon chambers
Solenoid magnet
Transition radiation tracker
Semiconductor tracker

Figure 2.1: Computer-generated view of the ATLAS Detector

ATLAS produces around three petabytes of RAW data per "nominal year" (i.e., the projected LHC duty cycle, see Table 2.1). This important amount of data needs to be written, filtered, transformed, processed, reprocessed, and analyzed, which requires a powerful computing infrastructure. CERN and all sites participating in any LHC experiment are linked through the Worldwide LHC Computing Grid (WLCG), a distributed computing infrastructure for the storage and analysis of data from LHC experiments [37]. These sites are organized in a hierarchical Tier structure. CERN is the central, data-taking site and is called Tier-0. About ten so-called Tier-1 sites are linked with Tier-0 through high-speed network connections and provide important storage and processing capabilities. Tier-2 sites are smaller data centers that mainly provide analysis and simulation capacity for physics groups. Each Tier-2 site is logically attached to a Tier-1. Additionally, smaller structures

Parameter	Value
E (Energy)	14 TeV (two 7 TeV proton beams)
L (Luminosity)	10^{34} cm^{-2} s^{-1} (design luminosity)
Collision rate	10^9 Hz p-p collisions at design luminosity, resulting from a bunch-crossing rate of 40 MHz
Trigger rate	200 Hz independent of the luminosity
Operation time	50000 seconds per day
Operation time	200 days per year

Table 2.1: Nominal LHC Operational Parameters and ATLAS Trigger Rate [9].

such as institute clusters are organized in Tier-3 centers. Figure 2.2 [25] shows the Tier structure of the WLCG sites. At the time of writing, this rather rigid structure is however being rethought by the ATLAS collaboration.

Table 2.1 summarizes the main LHC and ATLAS operational parameters. In terms of computing infrastructure, the Trigger rate is the main parameter to consider. ATLAS has a sophisticated trigger system, consisting of three levels: the Level-1 trigger (LVL 1), based on fast on-detector hardware components, selects max. 75 - 100 kHz out of the initial 40 MHz bunch-crossing rate. The subsequent two stages, the High-Level-Trigger (HLT), consisting of the Level-2 trigger (LVL 2) and the Event Filter, are software-based and run on dedicated online CPU farms; they further reduce the event rate to several kHz and a nominal rate of 200 Hz respectively. Those 200 Hz of most “interesting” events are eventually passed to offline processing. While the nominal trigger rate is 200 Hz, higher rates can be achieved during data taking. For a detailed description of the ATLAS Computing Model the reader is referred to [9].

2.2 From RAW Data to Event-Level Metadata: TAGs

RAW data from the detector is stored in a byte stream format and transferred from the event filter to Tier-0, the central ATLAS data processing unit at CERN. At Tier-0, the so-called Tier-0 Management System [38] provides the framework to process the data in several steps, as depicted in Figure 2.3. First, RAW data are reconstructed to Event Summary Data (ESD), which is intended to make access to RAW data unnecessary for the bulk of analyses. ESD, as all the subsequently produced data, is stored in an object-oriented format in ROOT files. Describing ROOT structures is out of the scope of this work, details can be found in [5]. Analysis Object Data (AOD) is then derived from ESD, by condensing the quantities most used in physics analysis. In Figure 2.3, temporary data products (before the merging steps) as well as stored data (right after the merging steps) are represented. Temporary AOD files are merged into final ones – the merging step reduces the number of data files. AOD is already more than a factor 10 smaller than RAW data, but still 100 kB in size per event. In order to allow a rapid filtering of events based on key physics quantities, so-called TAG files are produced at the end of the reconstruction chain. TAGs are event-level metadata that contain event descriptors, physics quantities, and sufficient information for back-navigation, i.e., for reaching a specific event in upstream data, based on a TAG selection. Table 2.2 summarizes

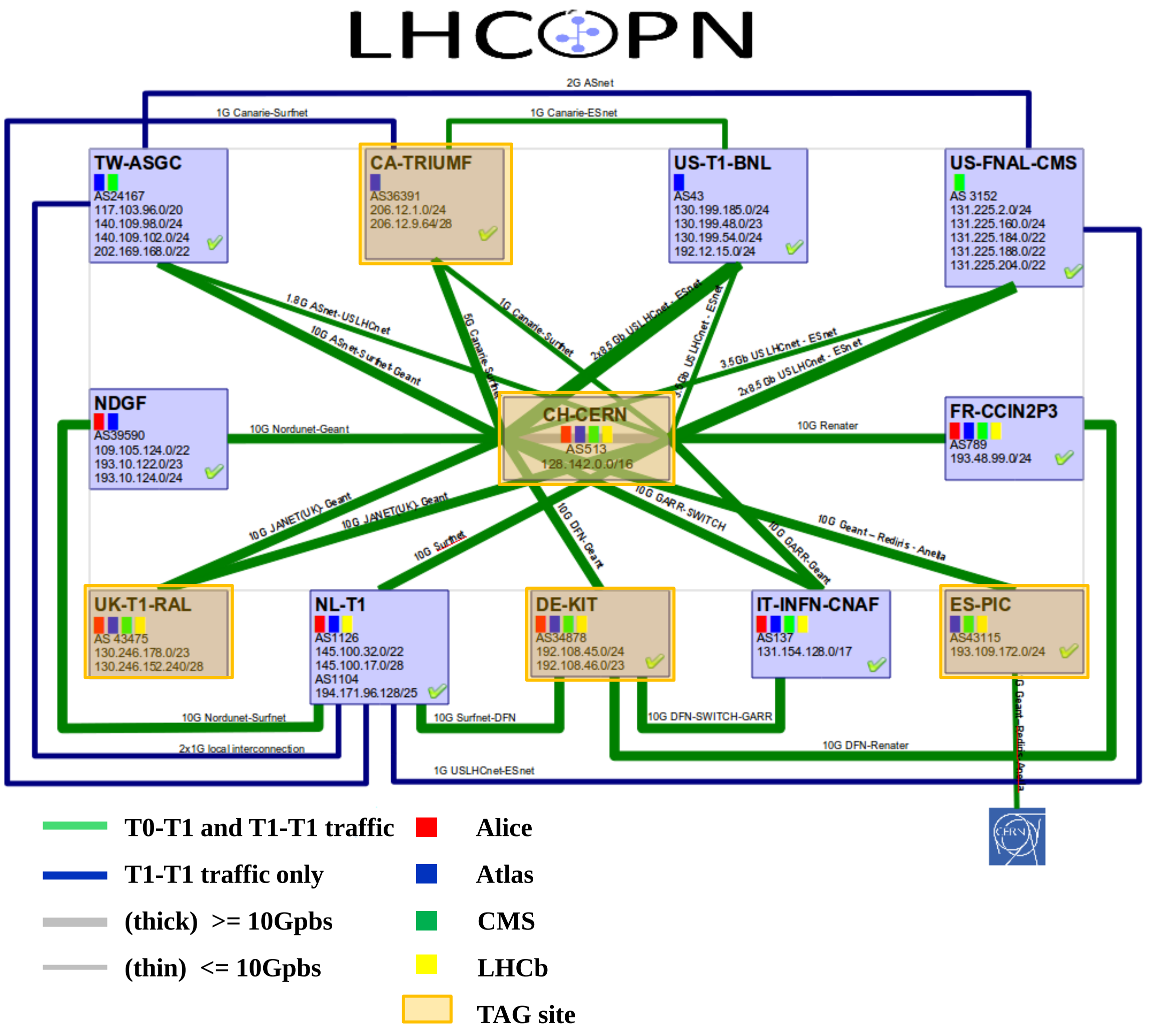


Figure 2.2: LHC Tier-0 and Tier-1 Sites and Network Overview

the approximate sizes of the main data formats in ATLAS [9]. Note that TAG, like RAW and as opposed to ESD and AOD, is not an acronym, but is used in analogy to *tags*, referring to keywords or metadata related to a piece of information and allowing to search for it.

TAGs are stored as POOL [82] Collections, with a physical back-end either as ROOT files or in a relational database. The latter are referred to as *relational TAGs*, as opposed to *file-based TAGs*. The Tier-0 management system uploads TAG data from files to several Oracle databases around the world, making them easily accessible through a services suite. The TAG upload and "posttag upload" are the last steps of the event reconstruction process at Tier-0, as shown in the top right corner of Figure 2.3. "Posttag upload" refers to database internal procedures and transformations applied to TAG data to make them efficiently accessible. An advantage in using databases is the ability to index the data as required, in order to allow fast and efficient queries.

In the remainder of this work, the focus is put on TAG databases as the source of TAG data.

Item	Value
RAW Size	1.6 MB
ESD Size	0.6 MB
AOD Size	100 kB
TAG Size	1 kB

Table 2.2: Nominal Event Data Sizes

2.3 TAG Data and Services

In order to gain an understanding of the TAG system and its challenges, it is important to briefly discuss the content of TAGs, the main use cases and the services provided to enable those use cases.

2.3.1 TAG Content

In a TAG record, an event is described by approximately 300 variables. The TAG content has originally been defined by a special task force in 2006 [6], and is since then under constant evaluation by the ATLAS physics and combined performance groups. The aim is to provide content that can be used for an efficient event preselection and covers all use cases defined by the physics groups. The exact content is beyond the scope of this overview, but the classes of variables are interesting to understand the TAG use cases. The variables can be classified as follows.

- **Event quantities:** include event number, Run number (a run/event number pair uniquely identifies an event), luminosity block and missing energy values.
- **Data quality:** bit-encoded words representing error codes per sub-detector.
- **Trigger information:** bit-encoded word specifying if an event passed a certain trigger or not.
- **Number of objects and their properties:** number of electrons, photons, muons, jets, etc. in the event, and basic object properties (e.g., momentum).
- **Physics TAG attributes:** words for each physics and performance group, free to encode in a "true/false" manner to mark an event as interesting for a specific analysis.
- **Collection information:** references to the same event in upstream data products, namely AOD, ESD and RAW data. These references (called Globally Unique Identifiers, or GUID) allow for back-navigation to the correct AOD, ESD and RAW file to retrieve the event.

TAGs are write-once, read-many – once written, the content is never updated. If already-processed RAW data are reconstructed with a new software version and new calibration, a new version of all data products, including TAGs, is produced. This process is referred to as a Reprocessing.

2.3.2 TAG Use Cases

In [32], the role of the TAG database (and more generally the TAG system) is described as "to support seamless discovery, identification, selection and retrieval of ATLAS event data held in the

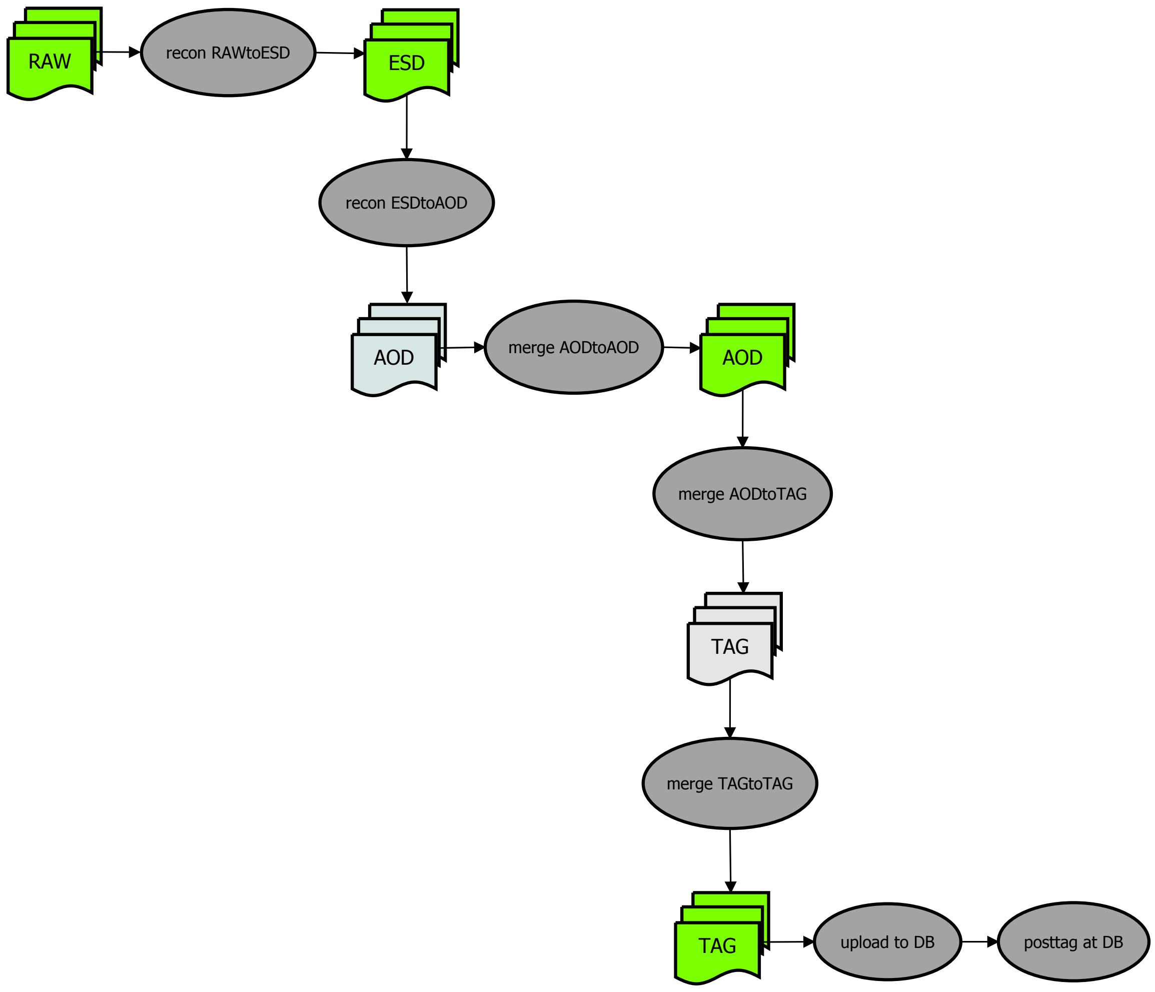


Figure 2.3: Data Reconstruction Chain, from RAW Data to TAGs [8].

multipetabyte distributed ATLAS Event Store.” TAGs are not meant for physics analysis, but for preselecting interesting events for further analysis. This preselection can be done on any of the TAG variables. From the selected events physicists can then navigate to the corresponding AOD, ESD or RAW data, to perform their specific analysis. As this analysis process can be very resource-intensive, it is preferable to run it only on events that are known to satisfy basic query predicates. An example TAG query is provided in Equation 2.2.

$$\begin{aligned} \texttt{RunNumber} \geq \texttt{52280 AND RunNumber} \leq \texttt{52304 AND} \\ (\texttt{LooseElectronPt1} \geq \texttt{20000 OR LooseMuonPt1} \geq \texttt{20000} \\ \texttt{OR TauJetPt1} \geq \texttt{20000)} \end{aligned} \tag{2.1}$$

According to [6], [30], [31] and recently arisen requirements, the main TAG use cases can be summarized as follows:

1. Browsing through the TAG data using a web interface (interactive queries). As new collision

events are recorded, the TAG database can be used to "check what data is there," in order to get a general overview. The TAGs are thus used as an index of the recorded data.

2. Using a TAG selection as input to a physics analysis. For example, let's consider that all the TAGs for a specific set of data (ESD, AOD) have been created. A physicist looks at the TAGs for this entire set of data and finds some interesting classes of events. He then wants to take the result of this TAG-based preselection and use it as input to a job which looks at the upstream AOD data. This can mean:

   (a) to locally extract a TAG file from the database and use it as input to an analysis job, or

   (b) to skim the data and directly get a RAW/ESD/AOD file containing only the events passing the provided TAG query.

3. Locate events based on a run and event number, and get the corresponding identifiers of the files containing these events. This functionality is referred to as *event lookup* and is integrated into central ATLAS Grid tools.

These generic use cases are addressed by the services of the TAG system, as described in the following two subsections. More specific use cases continually arise in physics groups, as the analyses evolve.

2.3.3 TAG Databases

As soon as TAG files are available, their content is uploaded to the TAG databases by the Tier-0 management system, using tools provided by POOL [82]. The TAG databases are relational Oracle databases. There are several deployments at several tiers of ATLAS, and their federation can be considered as a distributed database system, as the data can be queried transparently on any database, using a metadata registry (described in Chapter 4, 4.4).

Per year of data taking, the overall volume of relational TAGs grows by approximately 15 terabytes. Considering the operational parameters defined in Tables 2.1 and 2.2, a much lower volume is computed (Equation 2.3).

$$\begin{aligned} \text{Trigger rate} \times \text{seconds/day} \times \text{days/year} \times \text{TAG size} &= 200 \times 5000 \times 200 \times 1 \text{ kB} \qquad (2.2) \\ &= 2 \times 10^9 \text{ kB} \simeq 1.8 \text{ TB} \end{aligned}$$

However, these numbers do not account for indexes in the database, taking up a considerable amount of space. Additionally, the above parameters are valid for first-pass processing at Tier-0. However, data are regularly reprocessed, resulting in several versions of TAGs. Finally, TAGs of simulated events are also uploaded to the database. There are referred to as Monte Carlo TAGs.

Deletion policies are in place, so that unneeded data are being deleted regularly. However, at any given point in time during the experiment, several terabytes of TAGs are in each TAG database. Providing an Oracle service of this scale is a challenge and requires an important technical management effort. Much effort has thus been put in the optimization of data storage and query management. As part of the *posttag* process depicted in the right corner of Figure 2.3, TAGs are indexed, horizontally and vertically partitioned, and compressed.

For details on the operational challenges of the multi-terabyte TAG databases the reader is referred to [84].

2.3.4 TAG Services

The TAG system is composed of a suite of tightly coupled services, allowing access to TAG data and supporting the use cases defined in 2.3.2. The main TAG services are listed and briefly described below, with emphasis being put on providing an overview of the functionality instead of technical details.

TAG Database. Although being the data source, the TAG database is also considered as a service. See 2.3.3.

TASK Lookup. Service that allows looking up the TAG registry to locate a given set of data. TASK (TAG Application Service Knowledgebase) is described in detail in Chapter 4 (Section 4.4).

iELSSI. interactive Event Level Selection Service Interface, also referred to as *TAG browser*. It is a web interface, implemented using PHP and AJAX technologies, that allows browsing relational TAG data [107]. It requires a connection to one or more TAG databases and allows defining queries on all TAG attributes. The attributes are displayed in an ordered manner mimicking a typical selection process. Based on the entered selection criteria, it allows count queries and display of results, and can invoke the extract, skim and histogram services defined below. To properly display and process TAG information, it further uses the trigger decoding, extract XML builder and Lumiblock range builder services (see below). Figure 2.4(a) shows an example TAG query entered in iELSSI.

Extract. Service producing a TAG ROOT file containing the specified attributes of the TAGs for the selected events. The extract service uses POOL [82] utilities wrapped in Python. The output of extract can be used as input to a local or distributed analysis job, in the latter case using Grid job submission tools [30]. Extract can be invoked from iELSSI or directly from the command line, in both cases using an interface defined in XML. Figure 2.4(b) shows the integration of the extract service in iELSSI (panel "Retrieve without skimming").

Skimming. Service producing an AOD or ESD ROOT file for the events passing the TAG-based preselection. The main use case of the skimming service is that of a physicist who wants to first find interesting events satisfying a specified query, and then run some analysis on those events, without having to have any knowledge about where these events are, neither in terms of files, nor in terms of sites hosting the files. Figure 2.4(b) shows the integration of the skimming service in iELSSI (panel "Retrieve with skimming").

Event Lookup. The information contained in the TAGs allows determining in which physical RAW, ESD and AOD file a particular event is residing. As such it is the only event-level file reference. Event lookup is a service returning the GUIDs of the files containing specific events provided as input. It is integrated into Grid tools and used for determining the files needed for an analysis job.

Histogram. Java-based service allowing to draw histograms. It can be invoked from iELSSI and is used to create histograms displaying TAG variables.

Trigger Decoding. PHP service mapping a trigger name to the appropriate bit in the TAG trigger words. It is used by iELSSI to decode trigger words inside the TAGs. It can be invoked from a web browser or with a `curl` call.

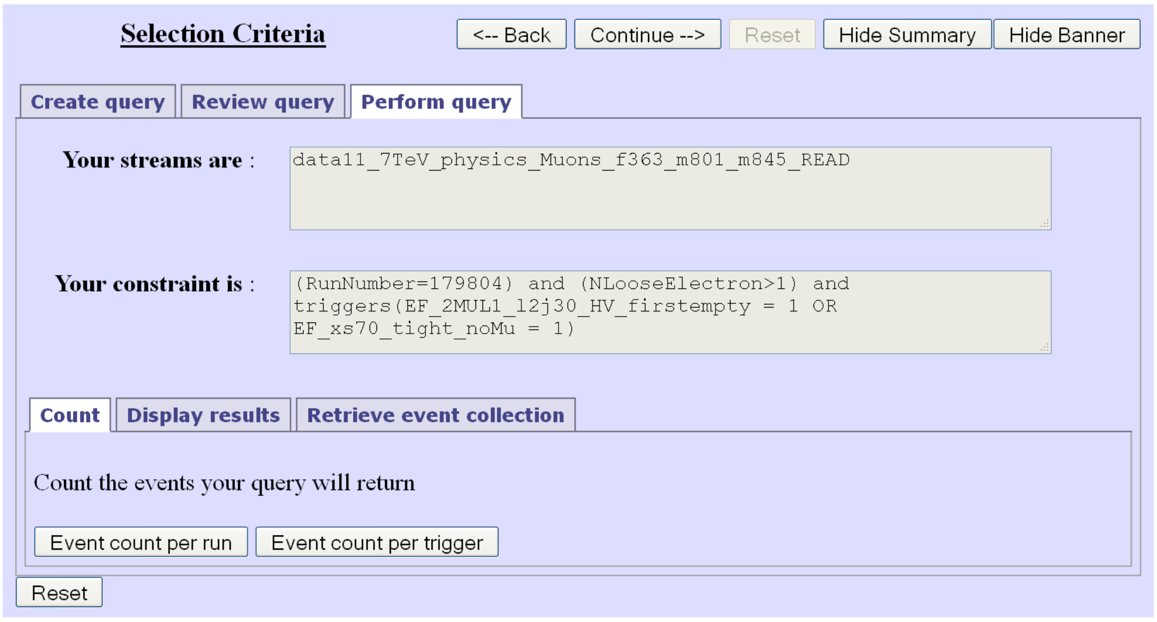
Extract XML Builder. Builds an XML file needed for extract. It is designed to be used by the command line extract application. It can also be invoked from a web browser or with a `curl` call.

Lumiblock Range Builder. Web service that builds the trigger active domain run and lumiblock range into an XML document. It is designed to be used by any independent application that needs the run-lumiblock range for its calculations.

runBrowser. Web-based interface that allows users to select runs based on all available conditions data (data describing the detector status) and conditions metadata [19]. Conditions data refer to data about the detector status at a given interval in time. The information presented in runBrowser is an integration of conditions and TAG data.

2.4 Typical TAG Workflows

The services described above are designed to be plugged together in order to build workflows tailored to allow an event preselection based on TAGs. In general, the input is a user-defined query, and the output can be a custom TAG or other file, that is then in turn used as input to a detailed analysis process. Example typical workflows are depicted in Figure 2.4. It shows the user actions and lists the needed services for displaying events that satisfy a certain user query. The user calls iELSSI, defines a query based on the available TAG attributes, and finally displays events. If he is not satisfied with the selection, he can refine the query and display events again, until the selection is satisfactory. In order to allow for this user workflow, several services need to be instantiated. First, the metadata registry (TASK) has to be called to locate the data. Second, a trigger decoding service and iELSSI have to be instantiated, so that the user can define his query. Finally, a TAG database has to be chosen to run the query on. The second activity diagram on Figure 2.4 shows the user actions and lists the needed services for extracting TAG data based on a query defined within iELSSI. An extract query can be spawned over several databases, either because no site hosts the entire set of required data, or for performance reasons. Several patterns (e.g., sequence, parallelism, loop) can thus occur in TAG workflows.

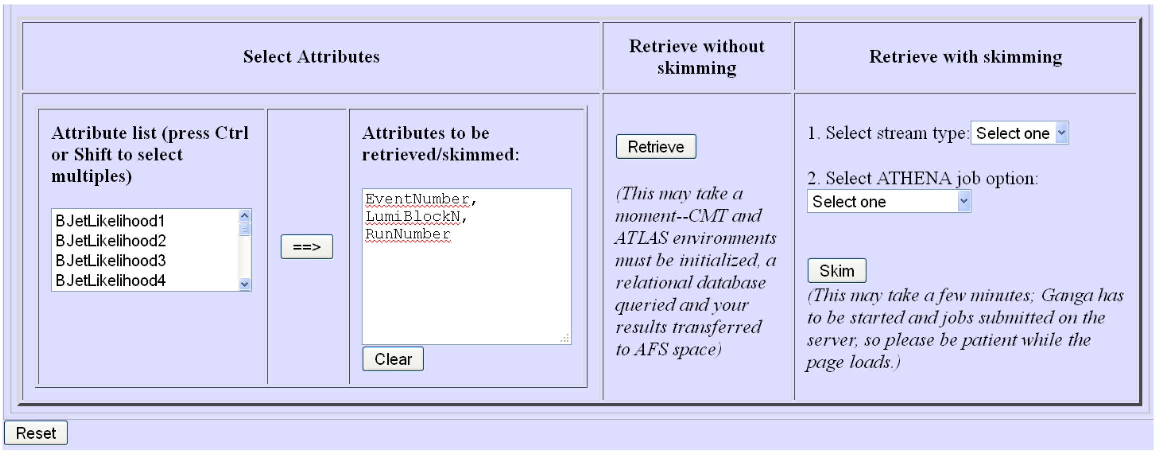


Your streams are : data11_7TeV_physics_Muons_f363_m801_m845_READ

Your constraint is : (RunNumber=179804) and (NLooseElectron>1) and triggers(EF_2MUL1_l2j30_HV_firstempty = 1 OR EF_xs70_tight_noMu = 1)

Count the events your query will return

(a) iELSSI Query Overview



EventNumber, LumiBlockN, RunNumber

(This may take a moment--CMT and ATLAS environments must be initialized, a relational database queried and your results transferred to AFS space)

1. Select stream type: Select one

2. Select ATHENA job option: Select one

(This may take a few minutes; Ganga has to be started and jobs submitted on the server, so please be patient while the page loads.)

(b) Extract and Skimming Integration in iELSSI

Figure 2.4: iELSSI Screenshots

2.5 Distribution of Data and Services and Resulting Challenge

At the time of writing, there are five ATLAS sites acting as TAG sites, four in Europe and one in Canada. They all host one or more TAG services as defined in Section 2.3.4. More sites are currently considering joining the TAG project.

Regarding the data distribution, there is a central unit at Tier-0 configuring the TAG uploads with regards to the sites the data are sent to. The general strategy is to have at least two copies of

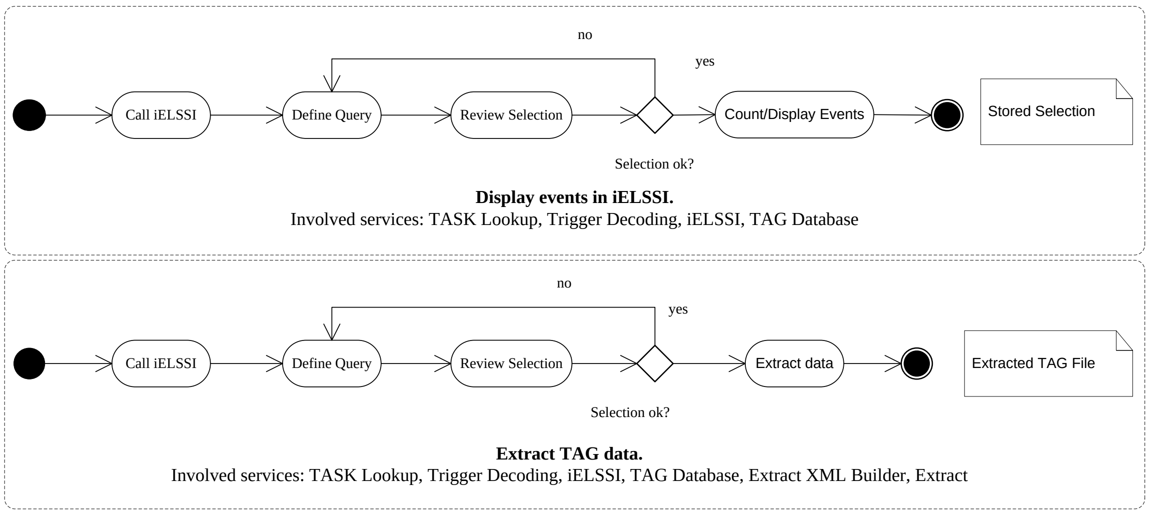


Figure 2.5: Typical TAG Workflows

each set of data for backup purposes, and the latest data available at more sites, because it is queried most frequently. The distributed TAG databases currently have an overall capacity of 80 terabytes. Data are grouped in so-called *projects* and *reprocessing passes*, and usually a whole reprocessing set it sent to a site, not only a fragment. However, such a fragmentation can happen and might even be emphasized in the future, when space limitations arise. A system keeping track of the data distribution in real time has been implemented in the context of this thesis work. The so-called TASK - *TAG Application Service Knowledge base* - is described in detail in Chapter 4 (Section 4.4). This knowledge base also records all available services, together with monitoring information and computed metrics. It allows treating all TAG databases as a single distributed database management system.

TAG sites are hosting other services than the TAG database on a voluntary basis, as resources are available. The minimum requirement is to have a set of web services per continent, in order not to suffer from high network latencies. However, it is preferable to have more service deployments, in order to allow for load balancing and fail-over.

To summarize, the TAG system is composed of several data sources, several abstract services and one or more concrete deployment(s) per service. All deployments of a service are identical in terms of functionality and software version, but have different QoS attributes, as they run on heterogeneous hardware, the hosting sites have different availabilities, different access policies, etc. Figure 2.6 is a simplified schematic representation of the distributed TAG system.

When a concrete workflow, such as one of the examples described in Section 2.4, is built to respond to a request, there are thus several choices for composing deployments. The choice of data sources and service deployments should be made automatically and based on rational decisions, conforming to the goals stated in Section 1.2 (minimize the response time per request and ensure a fair and efficient usage of all available resources). As TAG services are getting used more frequently, since data taking at ATLAS is a continuous process, and an important amount of data are available

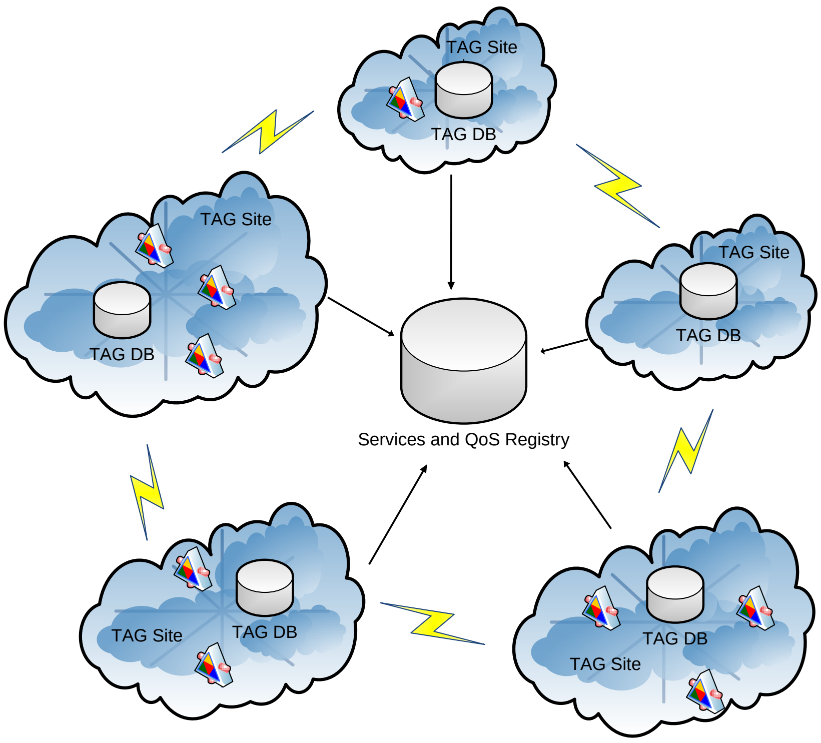
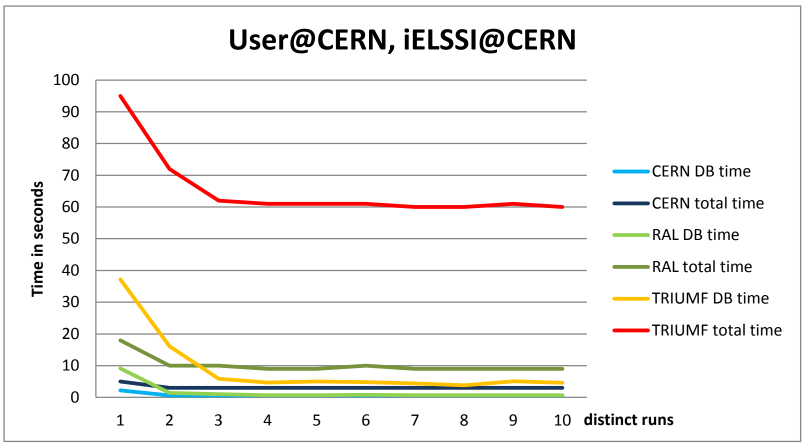


Figure 2.6: Distributed TAG System

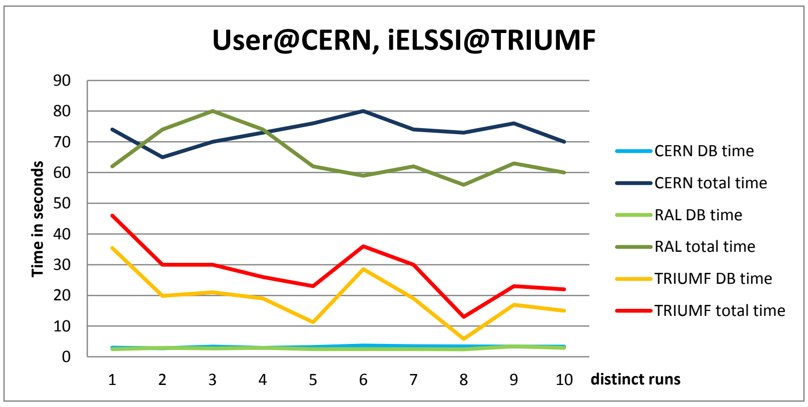
for analysis, a careful selection of services on a per-request basis is getting crucial in order to ensure an efficient event selection system based on TAGs. With the current setup, the problem size is rather small and it might be argued that no specific algorithm or approach is needed to address the service selection problem. However, the system is expected to grow, both regarding the number of sites and the number of deployments. Figure 2.5 shows the differences in execution times on the simple example of composing an iELSSI deployment with a TAG database deployment for an event count based on the query stated in Equation 2.4. This query is returning 9146 events satisfying the query out of a total of 36056886 events. CERN refers to the Tier-0 facility, TRIUMF is a data center in Vancouver, Canada, and RAL is the data center at Rutherford Appleton Laboratory in the U.K. The `Total time` is the time in seconds from the query submission to the display of the results in the IELSSI browser, thus encompassing the query time on the database and the time for sending the results over the network, building the page, etc. Figure 2.7(a) shows the values measured in ten subsequent runs with a user at CERN using the iELSSI interface at CERN and varying database back-ends. The decrease between the first run and the others can be explained by database caching. It can be seen that the total time when querying the database at TRIUMF is approximately 20 times higher than when the CERN database is queried, although the two database times (i.e., the actual query time on the database) do not differ much. The difference thus clearly lies in the link between CERN and the geographically far away TRIUMF. Figure 2.7(b) allows drawing similar conclusions. In this test series, the user issuing the query is still at CERN, but accessing iELSSI at TRIUMF.

It can be seen that, although the database time at TRIUMF seems to be higher than at CERN and RAL, the total time for the combination of the iELSSI at TRIUMF and the TAG Database at TRIUMF has the lowest total time. In summary, the values show important differences in the total response times, depending on the invoked deployments. These differences can be explained by different database server performances, different network latencies due to geographical distances, the place of the user, and time-dependent factors such as the current load on the invoked resources. A random or rank-based selection of deployments can thus not ensure an appropriate system response, making a more sophisticated deployment selection mechanism a necessity.

$$\begin{aligned} \texttt{Collection = data10\_7TeV\_physics\_Egamma\_r1774\_p327\_p333\_p372\_READ} \\ \texttt{AND RunNumber = 166094} \\ \texttt{AND NLooseElectron} > 1 \end{aligned} \tag{2.3}$$



(a) User at CERN, iELSSI at CERN



(b) User at CERN, iELSSI at TRIUMF (Canada)

Figure 2.7: Execution Times for Query Involving TAG Database and iELSSI

Before addressing the service selection challenge, several aspects have to be studied and taken into account:

- What are the components building up the TAG system? How are they mutually related?
- What system QoS attributes can be gathered, and which ones are important to be considered in the service selection process?
- What are the possible workflows and which patterns do they implement? Based on these patterns, how are the QoS attributes aggregated?

Chapter 4 addresses those questions, both in a generic way and tailored to the TAG system.

Service selection, and especially web service selection, is a widely studied research topic, and several approaches have been proposed, as will be discussed in Chapter 3. However, all system characteristics, requirements and optimization goals have to be studied in detail in order to find an appropriate solution approach. In particular, it is argued that in an experiment like ATLAS that is scheduled over several decades, use cases and optimization goals of an event selection system can change unexpectedly, and the service selection framework has to be able to adapt to these changes. In this thesis, a detailed study of the service selection problem is carried out, motivated by the challenges arising in the TAG system. The proposed solution approach is however generic enough to be applied to other systems.

Chapter 3

Background and Related Work: Service Selection in Heterogeneous Environments

Optimizing the selection of *things* conforming to defined objective functions and satisfying given constraints is a common and broadly studied problem in many applied research areas such as operations research, production planning, logistics, and many more. In computer science, it arises for example in the context of scheduling in distributed systems, database query optimization, and routing in networks. Through all of these examples, while the underlying problem is similar, the *things* – i.e., the considered entities to be selected –, the context, the objectives and the constraints differ. Additionally, depending on the concrete definition and context, the problems can map to slightly different mathematical models.

QoS-aware service selection is another example of such problems and has recently gained deep interest with the emergence of distributed, service-oriented systems, in which multiple service instances, differing only in their QoS properties, can be used for a given task in a service chain or workflow. This chapter defines the basic concepts and investigates related work, in order to precisely set the problem context and present a state of the art literature survey. While this chapter sets the basics, related work on more specific concepts used in the course of this thesis is presented in respective dedicated chapters.

This chapter is organized as follows. Section 3.1 defines the basic concepts used throughout the thesis. Section 3.2 defines the problem context and setting by comparing it to related problems. In Section 3.3 models of service-oriented systems and frequently-considered QoS attributes are discussed. Section 3.4 surveys the most common approaches to solve QoS-aware service selection problems. Finally, Section 3.5 summarizes research efforts and results in the area of multi-objective service selection optimization.

3.1 Basic Concepts

Terms like *Web Service* and *Service-Oriented Architecture* (SOA) are widespread in the area of computer science and beyond, but several – sometimes conflicting – definitions exist. It is thus important to set working definitions in the context of this thesis, in order to precisely state how the terms are used. To this end, this section provides definitions of basic concepts relevant to the understanding of this thesis.

Web Service. Although in this thesis we are referring to *services* in general, not only to Web services in the strict sense, the term Web service is often used, especially in the context of related work on Web service selection. The following definition from the World Wide Web Consortium (W3C) is adopted: "A Web service is a software system designed to support interoperable machine-to-machine interaction over a network. It has an interface described in a machine-processable format (specifically WSDL). Other systems interact with the Web service in a manner prescribed by its description using SOAP-messages, typically conveyed using HTTP with an XML serialization in conjunction with other Web-related standards." [101].

Service (extended service definition). In this work, "services" do not strictly refer to Web services implementing particular standards, but to a software component providing a functionality, independent of its internal realization and interfaces. W3C provides the following general definition of a service: "A service is an abstract resource that represents a capability of performing tasks that form a coherent functionality from the point of view of providers entities and requesters entities. To be used, a service must be realized by a concrete provider agent." [101]. A service can thus be a Web service, a Grid service, or an independent piece of software that can be invoked over a network. For instance, iELSSI as defined in 2.3.4 is considered as a service.

Service-Oriented Architecture (SOA). A software system composed of several components – or services – that can act independently or together to provide a defined overall functionality, is referred to as being service-oriented. In a SOA, the functionality is thus packaged in services, making the system flexible and reusability of software components easy. W3C provides the following definition of a SOA: "A set of components which can be invoked, and whose interface descriptions can be published and discovered." [101].

Service Selection. In case several concrete services (deployments) exist for a given functionality, one has to be chosen out of all possible or feasible ones. This requires the ability to determine what the possible ones are, which is usually done by querying a service *registry*. The process of querying a registry and choosing one concrete service (deployment) for a given task according to some defined criteria is referred to as service selection.

Service Composition. If several services need to be selected to respond to a given request, they need to be composed in order to operate together. This process involves defining inputs and outputs as well as exchange formats, i.e., the interoperability between the services has to be defined and instantiated. Two terms are recurrent in the area of service composition: *orchestration* and *choreography*, as defined below. The Business Process Execution Language for Web Services (BPEL4WS) is an example of a Web service composition specification.

Orchestration. Orchestration defines the sequence and conditions of service invocations and thus specifies an executable process [70]. It describes the view and control on the overall workflow from the perspective of one involved party.

Choreography. Choreography defines a collaborative view on a process and enables each party to describe its part in the interaction [70]. Specifically, a choreography specifies the public message exchanges between Web services, or between Web service orchestrations.

Workflow. A workflow is a sequence of steps (or services) to be executed. In this context, *sequence* does not necessarily mean one after the other, but the steps can be organized in patterns such as parallel split, exclusive choice, and arbitrary cycles. The concept of workflow patterns is detailed in [83]. More specifically, the result of a service selection and service composition is referred to as a *concrete* or *executable workflow*. The abstract specification of a sequence of services is referred to as *abstract workflow*.

In this thesis, service composition, orchestration and choreography are addressed only implicitly (because selected services need to actually work together), but the focus is put on the service selection process, i.e., the step preceding the composition. In the concrete application scenario, the interfaces between the services as well as the data and control flows are clearly defined and implemented. Therefore, once concrete service are selected to form a workflow, it is guaranteed that this workflow can be executed.

3.2 Overview and Comparison of Related Research Areas

In applied computer science, there are several research areas involving combinatorial optimization problems, such as (Web) service selection, scheduling, query optimization and QoS routing. Approaches to solve one problem can be applied or at least adapted to another one. The general problem studied in the context of this thesis is QoS-aware service selection. The three related areas mentioned above are shortly outlined in the following, and compared to QoS-aware service selection.

Scheduling. In general, scheduling refers to the allocation of limited resources to activities over time [74]. The term *activity* can refer to processes and threads, Grid jobs, steps in a production process, leisure activities, etc. It is thus a general problem occurring in many different environments. An activity could also refer to a service in a service selection problem. All the described scenarios can be viewed as sub-domains of a generic scheduling definition.

Query Optimization. Query optimization is used in Relational Database Management Systems (RDBMS) to determine the *best* way to execute a query. The challenge is thus to determine the most efficient or cost effective Query Execution Plan (QEP) from a multitude of possible QEPs. A cost-based optimizer parses the input query, generates equivalent expressions, and selects the expression with minimum costs, according to a cost function. The most common approach to perform query optimization is dynamic programming [49]. However, alternative approaches have been proposed, especially in order to address the fact that dynamic programming is inefficient for optimizing very large queries [49].

QoS Routing QoS routing is used in IP networks; its goal is to select routing paths based on QoS considerations. If several alternative paths exist, some can be overloaded and unable to support QoS requirements, while others have sufficient available resources in terms of network throughput. According to [44], the goal of QoS routing is to "provide algorithms that are capable of identifying such paths so as to satisfy the maximum possible number of flows with QoS requirements." Decisions about paths can be made based on QoS attributes of the available network links and on requirements for a given flow or request. The considered system is thus a network topology, and the QoS metrics relate to network links. The problem maps to a shortest path problem and approaches used to solve it include Bellman-Ford and Dijkstra algorithms [44].

The characteristics of the mentioned areas are summarized in 3.1. They present similarities in their objectives and underlying mathematical models, but differ in their application domains and in the objects they are operating on. They are clearly related; for instance an algorithmic approach for solving a QoS routing problem can be applied to service selection with only minor modifications such as the mapping of variables. In fact, some solution approaches can be found in all these problem domains. However, each domain also has its own requirements and challenges, beyond the pure mathematical problem formulation. The problem studied in this thesis qualifies as a service selection problem. This is thus the topic of the literature review. Establishing a state of the art of the other areas is beyond the scope of this work.

	Environment	**Objects**	**Result after Optimization**	**Mathematical model**	**Objectives**
Web Service Selection	SOA	Abstract and concrete services	Concrete workflow	MMKP, MCOP	Construct a workflow with maximized utility function while meeting QoS constraints.
Scheduling	Operating Systems, Clusters, Grids, etc.	Resources and jobs	Job-to-resource allocation	Queuing theory	Allocate processes or jobs to system resources in a way to load-balance the system and minimize resource starvation, while meeting QoS constraints.
Query Optimization	Database Systems	Database operators	Query Execution Plan (QEP)	Shortest path	Determine the optimal way to execute a given query on the existing resources and database objects (such as indexes).
QoS Routing	IP networks	Network links with associated QoS metrics	Network path	Shortest path, MCOP	Improve performance for QoS flows (likelihood to be routed on a path capable of providing the requested QoS) [44].

Table 3.1: Comparison of Related Research Areas

3.3 Modeling Service-Oriented Systems

3.3.1 System Models

In general, system models are used to identify and describe the individual components making up a system. Most authors studying the QoS-aware service selection problem define at least the concept of a *service class* and the concept of a *service* for describing the considered problem space. A service class allows grouping concrete services based on their functionality. All services inside a service class have the same functional properties, but differ in their non-functional properties. A service belongs to exactly one service class, and a service class contains 1 to n services. In some models, for example as in [56], a service is directly described by the vector of its attributes. The resources on which services are running are usually not defined. This is due to the fact that most works on the topic address the problem from the perspective of the service requesters, to whom the actual physical resources are unknown.

In Zeng et al. [106], the authors propose a service ontology defining the basic concepts used in their service composition model. (The concept of *ontology* is studied in Chapter 4.) Organizations wanting to provide a service have to publish a service description conforming to the agreed ontology. The authors define a `ServiceOntology` as a set of concepts (class `Concept`) used inside a domain and a set of service classes (class `ServiceClass`) defining the delivered functionality, i.e., the abstract services available. A service class is defined by attributes and operations. Relationship types between service classes include *specialization* and *composition.* Non-functional properties of services are described by quality criteria (class `QualityCriterion`). Each criterion is defined by a name, a type, and an expression describing the provenance and computation of the quality attribute. The service ontology definition is generic, and inside an organization multiple service ontologies can exist and in turn be shared and composed. To implement the ontology, the authors used IODT, IBM's Integrated Ontology Development ToolKit.

Wada, Suzuki and Oba [91] propose a UML profile for modeling non-functional aspects of service-oriented systems. They define five stereotypes, namely `Service`, `MessageExchange` (pair of request/reply), `Message`, `Connector` (connection between two services, including semantics of message transmission) and `Filter` (allows customizing the semantics of a message). The authors present a tool for model-driven development that accepts the proposed UML profile as input and outputs an application code skeleton. While the model specifies services and message exchange between them, it does not take into account quality criteria.

Broader, much more complete models have also been proposed. An example is the Common Information Model (CIM), a standard developed by the Distributed Management Taskforce [35]. The goal of CIM is to provide a common definition and understanding of IT systems, networks, services, and applications. It allows for extension and therewith enables vendors to exchange information between systems. It is composed of a *Schema* containing the model descriptions, and a *Specification* providing details about integration issues with other models. The Schema is a set of UML class diagrams grouped in packages such as `System`, `Database`, `User`, `Metrics`, and many others. The level of detail is very high, making it a full reference, but complex to implement. The `Core` package defines the basic concepts all other models are derived from. A simplified version of selected elements of the CIM Core package is depicted in Figure 3.1 [35]. `ManagedElement` is the root class from which all others are derived. For instance, a `System` and a `Service` are derived from the `EnabledLogicalElement` class. CIM provides a detailed, hierarchical representation of a generic computer system. It is however too complex and detailed for efficiently addressing service selection problems for which in general a less fine-grained system view is sufficient.

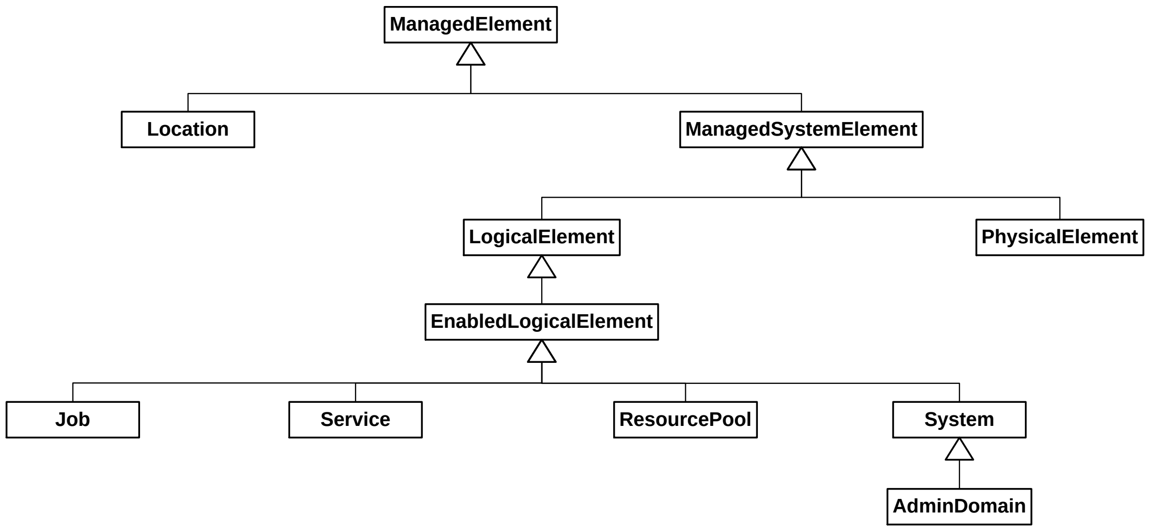


Figure 3.1: Selected Elements of the CIM Core Model

It has to be noted that in this chapter, when describing related work, the taxonomy originally adopted by the authors is preserved. In the remainder of this work though, the terms defined in Chapter 4 will be used exclusively.

3.3.2 QoS Attributes

QoS attributes need to be gathered and analyzed so that they can be used in QoS-aware service selection optimization. There exists a variety of attributes. In order to determine attributes of a system, it is useful to rely on a classification that guides through the process of gathering attributes. CIM [35] contains a type-based model for *Metrics*. Selected classes of the CIM Metrics schema are shown in Figure 3.2. In this model, attributes are basically categorized into discrete values and aggregated values. Classifications of QoS attributes are studied in more detail in Chapter 4 (Section 4.3).

An ontology of QoS attributes, named *QoSOnt*, has been proposed by Dobson, Lock and Sommerville in [36]. The authors distinguish two basic classes of QoS attributes, measurable and unmeasurable ones, the former ones having a certain *metric*. All attributes have a physical quantity of a given unit, and conversion rates are used for converting values between units. The classes form the “base QoS” layer of the *QoSOnt* ontology. In the attributes layer, the authors define QoS attributes for dependability and performance. The usage domains of the presented ontology are services and networks in service-centric systems. To show the applicability of the *QoSOnt* ontology the authors developed a tool for service discovery, differentiation and selection.

Papaioannou et al. [68] developed a QoS ontology language for Web services. The ontology defines a QoS attribute along the following classes of criteria: `QoSParameter`, `Metric`, `QoSImpact`, `Type`, `Nature`, `Aggregated`, `Node` and `Relationship`. All types of QoS attributes are modeled as sub-classes of `QoSParameter`. For example, `Performance` is defined as subclass of `QoSParameter`, and has in turn other subclasses such as `Throughput`. The full taxonomy is however not provided.

Chaari et al. [27] also proposed an ontology of non-functional properties. In their model, non-functional properties are broadly categorized into QoS properties and context properties. The detailed concepts identified by the authors are represented in Figure 3.3. Further, the authors define attribute measurement scales: nominal, ordinal, interval and ratio.

It is commonly agreed that QoS attributes are managed inside a so-called *QoS registry*, where the available metrics and their values are stored and can be queried at service selection and/or composition time. An example implementation of such a registry is provided in [63]. The QoS registry defined and implemented in the context of this thesis is described in Chapter 4 (Section 4.4).

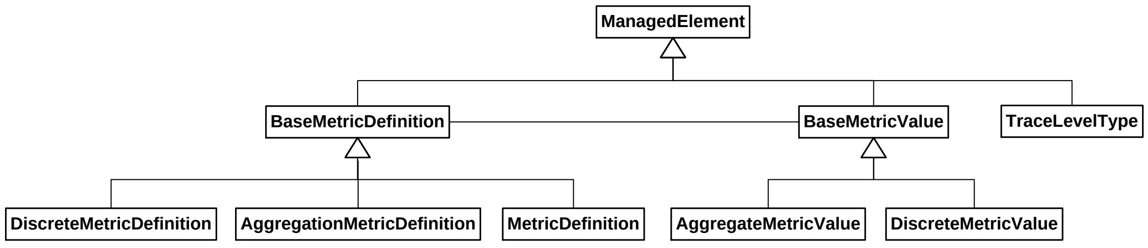


Figure 3.2: Selected Elements of the CIM Metrics Model

QoS attributes are used as input to and as decision variables in QoS-aware service selection problems. Depending on the considered system, more or fewer attributes can be defined and gathered. A variety of different QoS attributes are taken into account in related work. The most commonly considered attributes are summarized in the following:

Execution Time refers to the (estimated) time spent on the execution of a given service (deployment). It is also referred to as *execution duration* or as *response time*. For example considered in [3, 28, 63, 80, 102, 104, 105].

Costs refer to the amount of money a requester has to pay to the provider for a given service execution. Also referred to as *price*. For example considered in [3, 63, 69, 80, 102, 104, 105].

Availability refers to the relative uptime of a concrete service or resource, observed during a defined period of time. For example considered in [3, 39, 69, 102, 104, 105].

Reliability refers to the probability that a request is correctly answered and processed by a service. It is the ratio between successful and total executions. For example considered in [3, 39, 69, 80, 105].

Reputation is a measure for the trustworthiness of a service, mainly based on users' experience and ranking. For example considered in [3, 63, 80, 105].

Load refers to the utilization of a deployment or resource at a given time t, usually expressed in percent. For example considered in [28].

Latency expresses the delay in a system, from point A to point B, caused by the network. A common measure for network latency is the round-trip time, for instance between two servers. It is the network latency from one server to the other and back. For example considered in [69].

Bandwidth is a bit rate measure of available data communication resources in the network expressed in bits per second or multiples of it. For example considered in [3].

Throughput refers to the rate of successful delivery of messages over a network, usually expressed in bits per second or multiples of it. It is determined by the network bandwidth and the actual load on the network. For example considered in [3, 69].

More QoS attributes are mentioned in literature, but they are usually more complex to determine and quantify. Examples include *security* [80], *accessibility* and *regulatory* mentioned in [69]. Additionally, attributes based on users' feedback and ranking can be included into the list of QoS attributes.

For determining the QoS of a given workflow, the QoS values of the deployments constituting the workflow in question have to be aggregated. The function behind this aggregation is dependent on the patterns of the workflow and the nature of the QoS attribute. For example, the costs of a parallel execution of three deployments is the sum of the costs for each of them, whereas the availability of the same structure is determined by the deployment having the minimum availability value. Jaeger, Rojec-Goldmann and Mühl present aggregation functions for several QoS attributes per workflow pattern in [51]. Workflow patterns and aggregation functions for QoS attributes considered in this thesis are studied in Chapter 4 (Section 4.3.3).

3.3.3 Motivation for an Ontology for QoS-Aware Service Selection

Although several system and attribute models and ontologies exist in the area of service-oriented systems (as pointed out in the previous sections), they have not been designed to address QoS-aware service selection problems in systems comparable to the one studied in this work, which leads to the following shortcomings when applied to such problems:

- Scope: existing ontologies in the area of Web services, such as the W3C Web Services Architecture Ontology [100], mainly focus on Web service standards and message exchange protocols, rather than on the underlying basic system architecture, i.e., they are addressing a different problem domain. An ontology used for service selection problems should specify the components needed for the decision on how to build a concrete workflow. In this context, details on message exchange protocols are out of the scope.

- Level of detail: the level of detail has to be adapted to the scope and application domain. For example, the Common Information Model (CIM) provides a detailed specification of computing

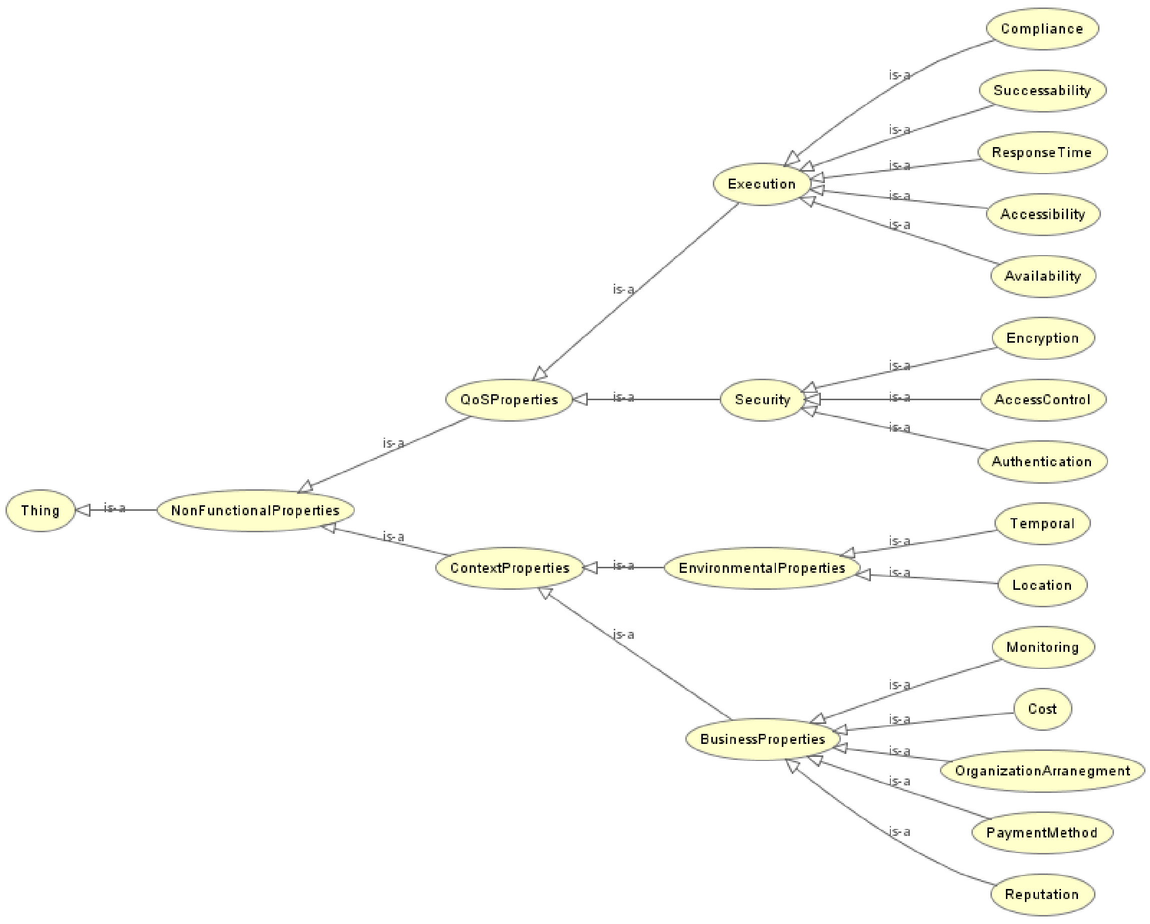


Figure 3.3: Classification of Non-Functional Properties by [27]

systems in general. However, the CIM schemas are very detailed, which makes them difficult to implement. Additionally, they have a much broader focus than the one needed in the context of service selection problems. For example, details about job configuration are out of the scope. Some concepts can be reused, but many have to be simplified. Other ontologies on the other hand lack details needed in service selection scenarios. For example, the ontology proposed in [27] does not address the question about how to gather, maintain, and update QoS attributes. The ontology presented in [106] has been designed to address service selection problems, however in this case the level of detail is rather low, and only a UML class diagram is provided as specification.

- Application domain: an ontology is usually tailored to a specific application domain. For example, *QoSOnto* [36] focuses on dependability attributes in service-oriented systems without central control instance, i.e., questions regarding compatibility, dependability and comparison of attributes (possibly provided in different units, depending on the provider publishing the information) are crucial ones, whereas they are not central in the system considered in this thesis.

- Availability: most ontologies are conceptually described, but their concrete specification (e.g., in the form of OWL files, cf. Chapter 4 Section 4.2 and Appendix A) is not made available, making it difficult to reuse and extend them.

For the above-mentioned reasons, and because an ontology should be as simple as possible for its specific purpose [81], a system and attribute ontology tailored to service selection problems should be developed. Such an ontology is presented in Chapter 4.

3.4 Approaches to solve the QoS-Aware Service Selection Problem

A variety of algorithms to address the QoS-aware service selection problem can be found in literature. This section provides an overview of recurring and widely studied approaches, rather than an exhaustive list. Figure 3.4 provides a classification overview of the described approaches.

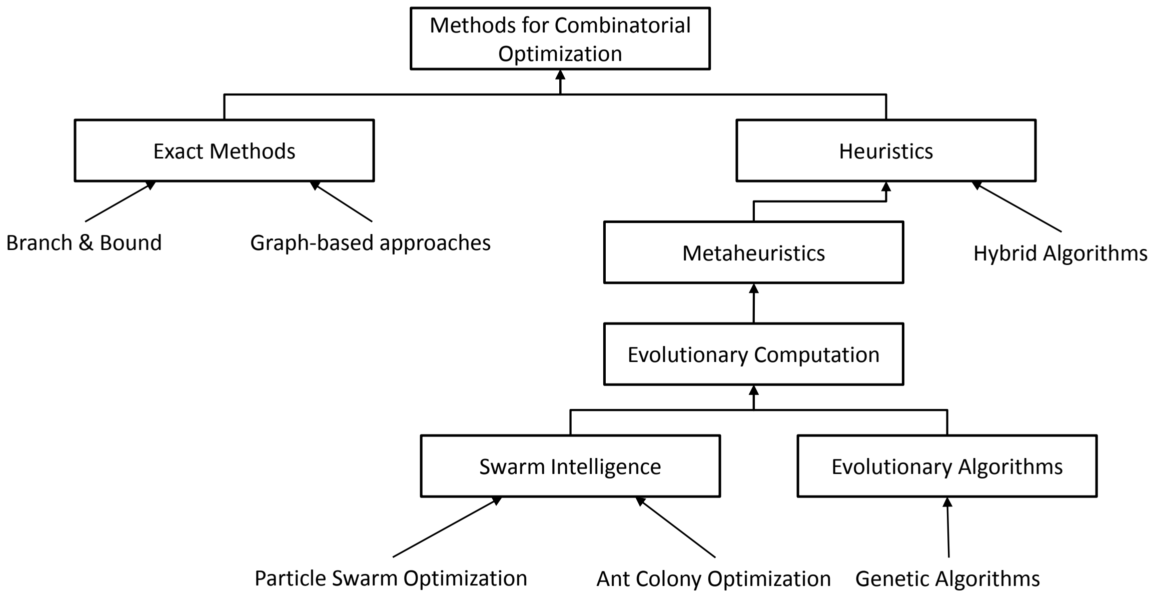


Figure 3.4: Overview of Optimization Approaches for Service Selection Problems

3.4.1 Linear Mixed Integer Programming

The general Mixed Integer Programming (MIP) problem can be formulated as [66]:

$$\max\{cx + hy : Ax + Gy \leq b, x \in \mathbb{Z}_+^n, y \in \mathbb{R}_+^p\}, \tag{3.1}$$

where $\mathbb{Z}_+^n$ is the set of nonnegative integral n-dimensional vectors, $\mathbb{R}_+^p$ is the set of nonnegative real p-dimensional vectors, and $x = (x_1, ..., x_n)$ and $y = (y_1, ..., y_p)$ are the variables. An instance of the problem is specified by the data (c, h, A, G, b), with c an n-vector, h a p-vector, A an $(m \times n)$ matrix, G an $(m \times p)$ matrix, and b an m-vector. All data are assumed in $\mathbb{Q}$. MIP is a mathematical model seeking at maximizing a given linear objective function while meeting linear constraints. Linear Programming (LP) is a special case of MIP in which there are no integer variables.

As Web service selection and composition is about maximizing a given utility function (minimizing a function is equivalent to maximizing its negative value) while meeting QoS constraints, it can be easily modeled as an MIP problem, assuming that the objective and constraint functions are linear.

For example, Zeng et al. [105] formulate a Web services composition problem and use LP methods to solve it. In their model, a concrete service composition is represented as an *execution plan* instantiating a path in a Directed Acyclic Graph (DAG). Each Web service has a quality vector associated with it. For each possible execution plan, the aggregated quality vector is computed, and an optimal plan can be selected based on Simple Additive Weighting (SAW). However, this method requires that all possible plans are generated. Given N tasks and M potential services for each task, the resulting computational costs for determining the optimal plan are $O(M^N)$. It is thus not a scalable approach. Therefore, the authors propose an LP-based technique to select the optimal plan, without having to actually generate all the possible ones. In the objective function of the LP problem five QoS attributes (price, duration, reputation, reliability and availability) and their respective weights are taken into account. Each variable y_{ij} has a value of 1 if the respective service s_{ij} is in the selected execution plan, and 0 if not. It thus represents the participation of a service in a plan. Constraints are formulated on execution duration, price, reliability, availability, and uncertainty of execution duration. The authors use an LP solver based on IBM's Optimization Solutions and Library to solve the stated LP problem. They finally compare the LP-based global planning approach to local service selection. Global planning results in better overall QoS values, but the computation costs are slightly higher than for local selection.

While QoS-aware service selection problems can naturally be modeled as MIP problems, computational complexity and scalability are important issues that can be addressed by hybrid approaches.

Alrifai and Risse [3] also depart from the observation that local service selection, whilst being efficient, does not allow proper handling of global QoS constraints. They propose a solution that combines global and local service selection optimization in order to take advantage of the better QoS results of a global approach and the better performance of a local optimization. To do so, the authors use MIP techniques. As in [105], the authors model the overall problem as an MIP problem. Because of the computational complexity that results in poor scalability, they propose decomposing the problem into two subproblems. In the first phase, the global QoS constraints are decomposed into local constraints on the component services level and they are sent to the involved service brokers. In the second phase, each service broker locally selects the best component service that meets the local constraints. The decomposition of global constraints into local ones is in turn modeled as an optimization problem, and MIP techniques are used to solve it. The decomposition aims to find a set of local constraints for each service class, ensuring that the QoS aggregation still meets all global constraints. This is achieved by introducing quality levels. The computational complexity of the resulting two-step model is determined by the number of abstract services, the number of global QoS constraints, and the number of quality levels and does thus not depend on the number of available concrete services, which makes the approach scalable. Evaluations show a significant improvement of the two-step hybrid approach over the global planning in terms of computation time. The achieved results are close to optimal.

Branch-and-Bound (BB) algorithms are often used to solve IP problems and have been widely applied to service selection problems. BB is an enumerative relaxation algorithm [66]. Figure 3.5 shows an enumeration tree a BB algorithm operates on. In this simple example it is assumed that there are three services with two deployments each. Each path from the root element to a leaf element is a possible composition of services $S1$, $S2$ and $S3$.

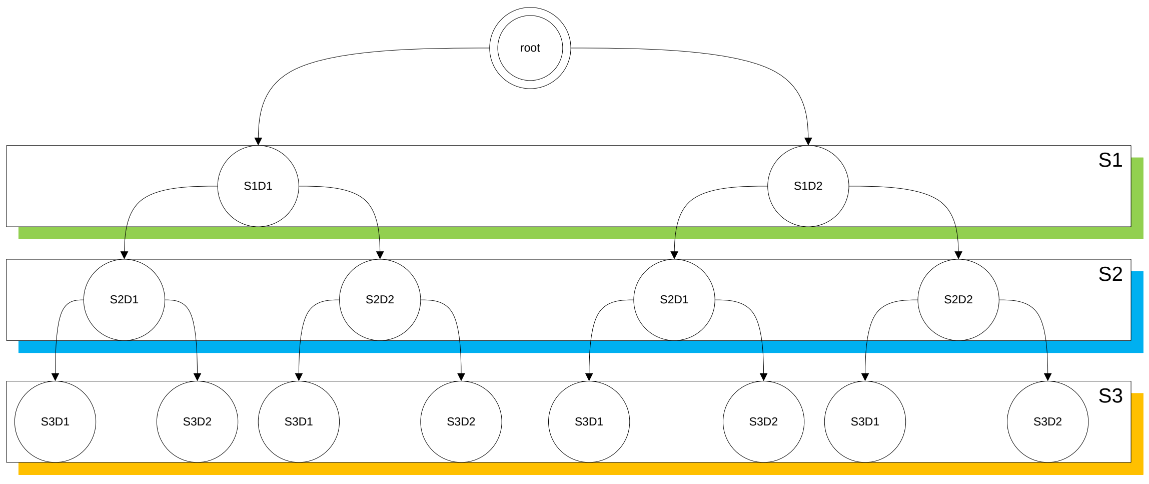


Figure 3.5: Total Enumeration Tree for Branch-and-Bound Algorithms

Yu et al. [104] propose BB-based algorithms for service selection both in the sequential flow and in the general flow model (including parallel and conditional branches). The sequential flow is modeled as an MMKP as defined in Chapter 1 (Section 1.1). The general flow is modeled as an IP problem. As BB algorithms are expensive in terms of computation time, heuristic approaches are also proposed by the authors.

A parallel BB algorithm for the QoS optimization of workflows is proposed in [56]. The authors also model the QoS-aware service selection problem as an MMKP. They introduce the concept of a *happiness measure* to define the user satisfaction with a given workflow. This measure is based on the aggregation of QoS attributes, and it is the value to be maximized. Solutions to the stated problem are represented as decision vectors $d = (d_1, ..., d_p)$, where each $d_v, v = 1, ..., p$ corresponds to a service selected for node v. The workflow structure as well as all available services are provided as input. The only global variable, `lbound`, defines the lower bound for the maximal happiness measure at each state of the algorithm. The happiness measure of each feasible solution constitutes a lower bound for the optimal happiness. Local solutions are computed on each node without taking the overall constraints into account, leading to a relaxation of the problem. In the parallel version proposed by the authors, each node in the decision tree is an instance of the main program and can be run on a separate Grid node each. A notable speedup is observed for the parallel implementation compared to the serial one if the overall computation time is sufficiently large (i.e., the problem space is above a threshold value) and at least three parallel processes are spawned.

3.4.2 Graph-based Approaches

An abstract as well as a concrete workflow can be represented as DAG. Yu et al. [104] propose converting an abstract workflow (represented as a *function graph*) into a *service candidate graph* (i.e., a graph with all possible paths to fulfill a given request) as follows [104]:

- every service candidate is a node in the service candidate graph;
- if a link from F_i to F_j exists in the function graph, then from every service candidate for F_i to every service candidate for F_j there is a link;
- every service candidate v in the graph has a benefit value of Φ and several QoS attributes;
- set network QoS attributes of the links between every two nodes;
- add a virtual source node v_s and a sink node v_d. v_s is connected to all nodes without incoming links and v_d is connected to all nodes without outgoing links. The QoS attributes of these links are set to zero;
- add QoS attributes of the node to its incoming links and compute the utility of every link.

An example service candidate graph is depicted in Figure 3.6. In this example, there are one to three concrete service candidates per service class ($S1$ to $S8$). One deployment from $S3$ and one from $S4$ are executed in parallel, and either one from $S6$ or one from $S7$ is executed (conditional choice). In the resulting DAG, each edge is associated with a set of QoS attributes and a utility value. The resulting service selection problem then maps to an MCOP (Multiconstraint Optimal Path Problem), where the goal is to determine the path from source v_s to sink v_d reaching the highest utility value, while meeting all QoS constraints defined in the specific problem setting [104]. The authors propose a multi-constraint shortest path algorithm to solve the optimization problem. This algorithm consists of several steps. First, the nodes are ordered topologically. Second, each node is visited and relaxed. On each node, all feasible paths (i.e., paths meeting all QoS constraints) from the source to the node are kept in memory. Alternatively, only a certain number of paths are kept, in order to reduce the memory requirements. The relaxation procedure is listed in Algorithm 1.

The proposed algorithms can be applied to sequential and general flow structures. The general flow structure includes non-sequential patterns such as parallel and conditional paths. Loops can be transformed into sequences by unfolding the cycles, given that the number of cycles is known. At merge nodes, QoS values as well as utility values need to be merged. At parallel merge nodes, since all services in all branches preceding the join are executed, QoS values need to be aggregated based on the properties of specific attributes. For example, costs are summed, whereas the minimum of all availability values is taken, or the maximum of all execution times. At conditional joins, the values of the chosen branch are propagated.

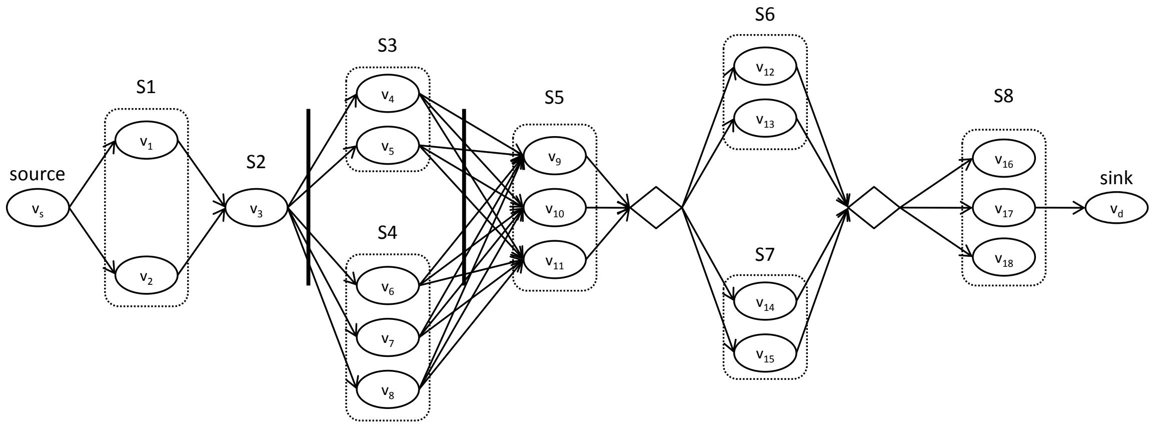


Figure 3.6: Service Candidate Graph (General Flow Structure)

3.4.3 Network Topology Approaches

Jin and Nahrstedt [53] studied the service selection problem in large networks. Following the network nomenclature, the authors call the challenge *QoS service routing*. The authors define a *service path* as an end-to-end network path containing a given service sequence. They further distinguish *service unicast* (one-to-one routing scenarios) and *service multicast* (one-to-many routing scenarios). In the latter case, multiple end users are receiving data through a workflow, based on individual capacities and requirements. The authors put an emphasis on the scalability of service routing by adopting a distributed routing approach. They argue that in the current Web scale, the resulting network is too big for a centralized monitoring and planning approach.

A hop-by-hop approach is described to address the QoS routing. Each hop sends a QoS probe message to all the adjacent nodes in a DAG in which the concrete services constitute the vertexes and the edges are the network links between the concrete services. From all the instances satisfying prior defined conditions, the one leading to the most delay-efficient service path is selected. Considered conditions include network bandwidths and machine capacities. The shortest service path is determined by applying a shortest path algorithm on the DAG. This approach is referred to as *Geometric Location Guided* (GLG), as opposed to *Local Resource Amplest* (LRA). In the LRA approach, the next hop is the one having the best aggregated QoS value computed based on bandwidth, machine resources, and machine availability. Because it relies on local heuristics and does not consider location information, LRA results in long and inefficient services paths. The authors propose two combined approaches, namely *LRA-GLG* and *GLG-RLA*, differing only in the application order of the two routing approaches.

Simulations have been carried out to evaluate LRA, GLG and the two combined approaches, using several metrics such as link utilization, machine utilization and service path length. Results show that GLG performs best regarding shortest path metrics (as designed), while LRA allows keeping balanced network and machine loads. In general, over all considered metrics, the best results are achieved with LRA-GLG.

These results are relevant to the TAG problem setting, as the LRA-GLG approach helps balancing the tradeoff between path lengths and load balancing in service graphs, which can be mapped to

Algorithm 1: Relaxation Function of the Multi-Constraint Shortest Path Algorithm

```
1  $\mu, v$: vertexes on the DAG;
2  $Q(p)$: aggregated QoS of path $p$;
3  $\mathcal{F}$: utility of edge $[\mu, v]$ or path $p$;
4  $P(v)$: list of paths from the source to node $v$ that satisfy all QoS constraints;
5  if ($\exists\alpha, Q^\alpha > Q_c^\alpha$) then
6      return
7  end
8  for each $p \in P(v)$ do
9      if $\mathcal{F}(p) > \mathcal{F}$ and $\forall\alpha, Q^\alpha(p) \leq Q^\alpha$ then
10         return
11     end
12     if $\mathcal{F}(p) < \mathcal{F}$ and $\forall\alpha, Q^\alpha(p) \geq Q^\alpha$ then
13         remove $p$ from $P(v)$
14     end
15 end
16 Add path $p'$ with attributes $[\mu, Q, F]$ to $P(v)$;
```

minimizing the execution time and maximizing the throughput of the TAG system. However, as the TAG system has a much smaller scale than the one considered in [53], a centralized global optimization approach can be adopted.

3.4.4 Game Theory and Bidding

According to [11], "Game theory concerns the behavior of decision makers whose decisions affect each other." It analyzes behavior and decision making from a rational point of view and can be applied to as diverse areas as economics, political science, evolutionary biology, and computer science. In the latter field, game theoretic approaches have for example been successfully applied to scheduling and load-balancing problems in Grid computing [59, 78]. Kwok [59] states that as the Grid scales up, the machines cannot be considered as *cooperative* anymore, i.e., the peers in a distributed system might not want to cooperate with each other. The scheduling problem can thus be modeled as a noncooperative game in which every player independently and selfishly chooses a strategy in order to optimize its payoff. The payoff is the numerical outcome of the payoff function that maps a utility to each strategy. The ultimate goal of a noncooperative game is to find an equilibrium, the best-known being the *Nash equilibrium*. In this equilibrium state, no player can benefit from changing its strategy when the other players keep their strategies unchanged.

Game-theoretic models and techniques have equally been applied to QoS-aware service selection problems [39, 75]. Esmaeilsabzali and Larson [39] study the QoS-aware service selection problem in a game-theoretic setting from the service provider's point of view. They model the problem as a multi-dimensional single-round auction that can be repeated many times. It is multi-dimensional because several attributes are considered for making a choice. In their study, the authors consider two quality attributes, namely availability and reliability. Price is considered separately, as a special attribute. In case there are several providers for a given service, each submits a bid stating the proposed price for providing the service. The service requester then selects a bid according to a utility function depending both on the price and on the advertised QoS attributes. More specifically, service providers propose a contract defined as $\langle q_{iR}, q_{iA}, p_i, N_i, f_i(t) \rangle$, where q_{iR} and q_{iA} are the minimal guaranteed values for reliability and availability of service i, respectively, p_i is the price, N_i is the maximum number of requests in a day, and $f_i(t), 0 \leq t \leq 24$ is a function specifying the maximum number of concurrent active services at any given point t in time (hour) per day. A service provider can only win the contract if he "promises" to fulfill it. The determination of the quality attribute for the service providers is interpreted as an equilibrium problem, and a dominant strategy that maximizes the provider's benefit is derived. The service allocation itself is then modeled as an auction, and a winner determination algorithm based on dynamic programming is proposed. It is noteworthy that the winner determination problem can be directly mapped to a knapsack problem, therefore similar approaches than the ones presented above can be applied.

Shen and Fan [75] motivate the use of a game-theoretic approach by the fact that for time-sensitive services the waiting time is not only dependent on the provider's performance, but also on the number of incoming requests (the queue length), i.e., the selection strategies of all other system users. Each user thus has to compete with the others for resources. This can be modeled as a noncooperative game. Based on the observation that pure strategies, i.e., strategies in which all users tend towards the best evaluated provider, lead to an overload on one or few provider(s) while leaving others almost idle, the authors propose a cooperative mixed strategy to the service selection problem. In this strategy, the user selects the service promising the minimum execution time only with a certain probability. Simulations have been carried out that show that the adopted approach shortens the average waiting time and queue length, and ensures a load-balancing among the providers. It is however based on the assumption that the request arrival rate follows a Poisson distribution.

Cheung et al. [28] propose a bidding-like approach to address load-balancing in service selection problems. For an incoming request, each service provider hosting a requested service computes a bid value based on the estimated service time and the current system load. Each provider sends its bid value to a broker that then selects a concrete service according to a probability distribution. Experiments show that this approach allows adapting to unexpected load of resources, making it appropriate for the use in dynamic environments.

3.4.5 Evolutionary Approaches

Evolutionary Algorithms (EA) have been adopted to solve QoS-aware service selection problems [22, 46, 52, 62, 72, 90]. The basic underlying idea is to use evolutionary, mainly genetic, algorithms that mimic processes from natural evolution to converge a population of possible solutions (i.e., concrete workflows) to an optimum. As the approach adopted in this thesis is also based on genetic algorithms, this part of related work is studied in detail in Chapter 6 (Section 6.5), after having defined all terms and basic concepts needed for a deeper understanding.

3.4.6 Swarm Intelligence Approaches

Swarm Intelligence is a technique originating from Artificial Intelligence and is concerned with the design of intelligent multi-agent systems inspired by the social behavior of animals such as ants, fish, and others [45]. There are two main techniques: Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO).

PSO is an optimization method mimicking social behavior of animals or insect swarms [45]. It has first been introduced by Kennedy and Eberhart [55]. The underlying idea in PSO is that individual particles of a swarm represent potential solutions to a given problem, much like individuals of a population in evolutionary algorithms. These particles move through the problem search space by applying functions taking into account the particles' position and velocity, allowing them to evolve towards an optimal or near optimal solution. Specifically, the velocity of each particle is iteratively modified by its best position found so far, and the best position of its neighbors. Algorithm 2 shows a simplified PSO algorithm, where x_i is the position of particle i, p_i denotes its best personal position, and p_g is the best position of particles in its neighborhood [45]. PSO have been applied to many problems, including scheduling, multi-objective optimization and dynamic problems.

Algorithm 2: Particle Swarm Optimization Algorithm

```
initialize random swarm;
repeat
    for each particle i do
        if $f(x_i) \geq f(p_i)$ then
            $p_i \leftarrow x_i$
        end
        $p_g = \max(p_{neighbors})$;
        Update velocity;
        Update position;
    end
until termination condition true;
```

PSO has recently been applied to QoS-aware service selection problems [54, 79, 102]. In [54], the authors model a multi-objective service selection problem taking into account cost, time, reputation and reliability, and design an algorithm based on multi-objective PSO. The approach is compared to a genetic algorithm and experiments show that the PSO-based approach has an improved runtime performance. However, no details are provided on the implementation and parameters of the genetic algorithm. Sun et al. [79] propose a hybrid service selection approach. First, they use fuzzy logic control to decompose global QoS constraints into local ones, then they perform local optimization based on PSO. The idea behind this approach is close to the ones presented by Alrifai and Risse in [3].

The second main technique of swarm intelligence is ACO. ACO algorithms are inspired by the foraging behavior of ant colonies, characterized by the indirect communication between ants via pheromone trails that indicate the shortest path between their nest and food sources [45]. Indeed, when moving from their nest in order to search for food, ants leave pheromones on their trail. The ants arriving first at the food source probably took the shortest path, and the probability that they will choose this same path to return is higher than for any other path. Thus, this trail will have the highest pheromone concentration, attracting the ants on their next trip for food. The pheromone on other trails evaporates over time, when no new pheromone is spread there. ACO algorithms mimic this behavior. Ants represent partial solutions. The central component of the algorithm is the so-called *pheromone model* consisting of a set of values. Mathematically, this model corresponds to a parameterized probabilistic model. In an ACO algorithm, candidate solutions are first constructed using the pheromone model. Second, these solutions are used to modify the pheromone values (referred to as *pheromone update*), in such a way that future solutions are concentrated on promising areas of the search space, leading to good solutions.

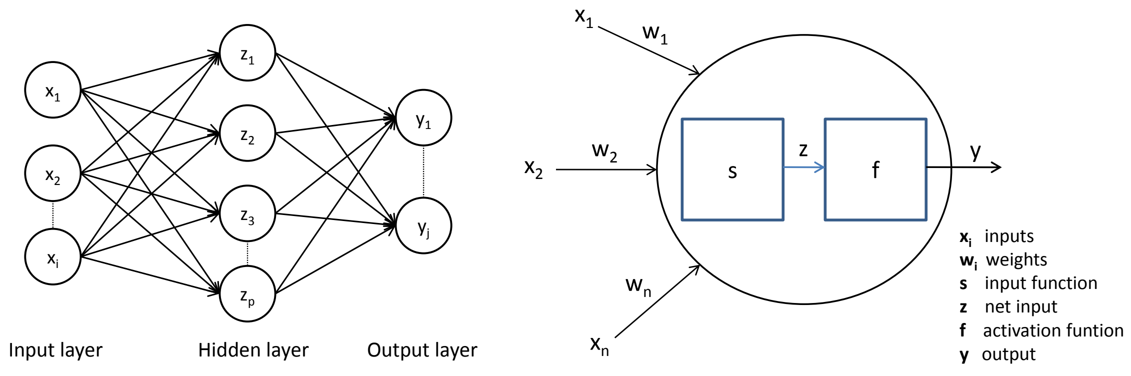
In [94], Wang et al. apply an ACO approach to the service selection problem. The ant nest S is the virtual start of the service composition, and the food place F corresponds to the last service in the workflow. The goal is to find the shortest path between S and F, and the ants have to travel to each service node exactly once. First, every ant calculates a transition probability when moving to the next service. Second, the pheromone of the path is calculated using a quality function based on five QoS attributes, response time, price, expire time, availability, and security level. The authors show that their ACO algorithm reaches at least 95% of the optimum in all their test runs. However, there is no comparison with a similar approach in terms of runtime scalability. Zheng et al. [108] also propose an ACO-based approach to the service selection problem, and they include parallel workflow structures in their model. In their algorithm, ants are initially positioned on the source vertex of a Web service composition graph defined as a DAG including OR- and AND-vertexes. Each ant has to find a path from the source to the destination vertex. Specific state transition rules are applied on OR vertexes, while on AND vertexes ants are cloned so that each path is chosen by one ant. Local updating rules define how an ant updates the amount of pheromone on visited edges, and global updating rules are applied once all ants have reached the destination.

3.4.7 Artificial Neural Networks

An Artificial Neural Network (ANN) is an information-processing system inspired by biological neural networks whose main components are dendrites, soma and axon. An ANN consists of neurons (processing elements) and weighted connections between them. It is further characterized by its method of determining the connection weights, and its activation function [41]. ANNs can be applied to a variety of problems, including pattern recognition and constrained optimization problems. Figure 3.7(a) depicts a simple ANN consisting of an input layer, a hidden layer and an output layer. Figure 3.7(b) shows the simplified mathematical model underlying ANN.

ANNs have recently been used to address QoS-aware service selection problems. Cai et al. [20] design a neural network predicting controller that evaluates all possible service candidates according to knowledge from previous selections, service attributes, and context information. Four objectives are defined: maximize the performance from the client's perspective, while satisfying QoS requirements; maximize the service efficiency and load balancing; minimize the jitter, delay and packet loss in the network; and minimize the time spent in the application. The results of the evaluation are then transferred to a service selection controller that selects the actual best service and returns it to the client. For the evaluation, a Back Propagation ANN is used, consisting of multiple inputs, one hidden layer, and a single output (the result of the evaluation function). All factors affecting the evaluation are used as input. Four kinds of input variables are considered: status parameters of the affected servers (use of memory, CPU, etc.), status parameters of the network (network load, bandwidth, etc.), collected parameters from past executions, and reliability measures. The authors name the following advantages in using an ANN for their service selection problem: ability to include context information, ability to include information from previous selections and compositions, scalability and efficiency. The proposed approach has been implemented and evaluated in an ubiquitous Web services environment. Simulations show, among other results, that the proposed approach outperforms two comparable approaches (one based on genetic algorithms and fuzzy logic, and one based on trust mechanisms) in terms of service selection reliability.

Al-Masri and Mahmoud [1] use Back Propagation ANNs to classify services into categories (Platinum, Gold, Silver, Bronze), based on their QoS attributes such as response time, throughput, availability, and reliability. As above, one hidden layer is used, and sigmoid activation functions are defined for the neurons. An evaluation has been carried out based on a publicly available collection of QoS metrics of real Web services. Simulations were run to determine the best network configuration. The configuration leading to the highest performance rate (defined as the ratio of correctly classified services to total services) has then been used for training the network and running further tests. The authors note that the learning rate and the number of nodes in the network are crucial values that impact the system performance. It has further been observed that the more QoS parameters are taken into account, the higher the performance of the ANN. No comparisons to other approaches have been carried out. The authors conclude that the proposed ANN is capable of correctly classifying Web services in a ranked manner, based on published QoS attributes.



(a) Multilayer ANN (b) ANN Mathematical Model

Figure 3.7: ANN Components and Simplified Mathematical Model

3.5 Multi-Objective Service Selection Optimization

Service selection problems, as many other optimization problems, can have more than one objective function. Objectives are usually competing, i.e., the best solution with regards to one objective can be the worst with regards to another objective. A *good* solution is thus a *compromise* between the various objectives. For example, in a service selection scenario one might want to minimize the expected execution duration while also minimizing costs. Assuming that better performing services cost more than less performing ones, a decrease in execution time will result in an increase of the related costs. These problems are referred to as Multi-Objective Optimization Problems (MOOP) and are discussed in Chapter 5 (Section 5.4). In the following, recurring competing objectives and approaches to solve MOOP in service selection scenarios are briefly outlined.

Several authors formulated specific service selection challenges as multi-objective optimization problems [62, 72, 90]. Liu et al. [62] describe a scenario with two objectives, namely minimizing the execution time and minimizing the costs, and impose constraints on reliability and reputation. The authors propose a strategy for global optimization of dynamic Web service selection based on a multi-objective genetic algorithm. Qiqing et al. [72] aim at finding a concrete workflow that minimizes cost and time, and maximizes the overall reliability while meeting user-defined QoS constraints. To address this multi-objective optimization problem, they propose a Multi-Objective Ant Colony Optimization (MOCACO) algorithm. The authors compare their algorithm to a multi-objective genetic algorithm proposed in [62] and show that, for different test settings, MOCACO outperforms the GA both in runtime performance and in the solution quality. An evolutionary approach is also presented in [90], where minimizing costs and maximizing throughput are the two competing objectives.

Yu and Bouguettaya [103] propose using multi-objective optimization techniques to compute *service skylines*. A service skyline is a small set containing the *best* services regarding defined criteria. The aim is to return to the user a set of services that satisfy his requirements and represent good (non-dominated, cf. Chapter 5, Section 5.4) solutions to multiple objective functions. This way, the user can himself choose a service, but is not confronted with the whole set of available ones. The concept of a service skyline is inspired from the concept of *top-k queries* in database systems.

Related work on multi-objective service selection optimization using EA is studied in more detail in Chapter 6 (Section 6.5).

Chapter 4

An Ontology of Components and Attributes of Distributed, Service-Oriented Systems

Many modern computing systems, be they for scientific or business applications, are designed as service-oriented systems, i.e., self-contained pieces of functionality are provided in individual services that can act independently or together. Additionally, for performance, scalability, and reliability reasons, they can be distributed across geographical sites and even organizational boundaries. Indeed, components of a service-oriented model can be easily distributed due to their self-containment. However, such a system also requires a high level of management, in particular if the distributed units are heterogeneous, i.e., not necessarily pure standard-conform Web services that are described in a SOAP interface and can be discovered via UDDI. Therefore, it is important to have a mechanism to *describe* and *monitor* such systems. To this end, this chapter presents a system and attribute ontology and classification. Its purpose is to identify the building blocks of heterogeneous, service-oriented systems and the attributes characterizing those blocks. The proposed models are customized to the TAG system, showing their applicability to a real-world example. Finally, a concrete implementation of a service registry – the so-called TAG Application Service Knowledge Base (TASK) – is described.

This chapter is organized into sections as follows. In Section 4.1 the purpose and scope of ontologies are outlined, and the methodology adopted in this chapter is described. Section 4.2 presents the generic system ontology and its application to the TAG system, defining the individual system components and their interactions. In Section 4.3 system attributes, specifically QoS attributes, are studied in detail. A QoS attribute taxonomy is presented and applied to the TAG system, and attribute aggregation functions are defined. Section 4.4 details design and implementation considerations of TASK. Finally, Section 4.5 summarizes the key notions and concludes this chapter.

4.1 Methodology

Many different parties are usually involved in the design, implementation, operation and support of a large-scale, distributed system. In the TAG use case for example, system engineers and developers are members of the ATLAS collaboration, working in different countries, time zones, and institutions, although all belonging to the same Virtual Organization (VO), namely ATLAS. The collaborative aspect and efficient communication structures thus play an important role. Additionally, all contributed pieces of software have to work together. This is referred to as an *interoperability requirement*. It is thus crucial that all involved parties have a common understanding of the system and its scope and building blocks as well as their interactions. Therefore, it is beneficial to build and agree on a system model and related vocabulary. This eases communication and future software contributions as well as the adoption of optimization strategies on the existing system.

Ontologies are a means to achieve the above stated goals. An ontology is a shared understanding of a domain of interest, generally viewing this domain as a set of concepts, their definitions, and their inter-relationships [81]. It defines a structured namespace built upon hierarchies that sets the semantics of the system it has been designed for. Its primary benefit is to define a common vocabulary that has to be used by all those interacting with the system. The benefits of defining and using ontologies in the area of service-oriented systems and service selection have been pointed out by Yu and Bouguettaya [103] in their work on foundations for an efficient selection of Web services. The authors characterize an ontology as *shared* (i.e., the involved parties have to agree on it), *explicit* (i.e., all terms are explicitly defined) and *formal* (i.e., described in a well-defined and unambiguous model or specification language). The definition and representation of an ontology range from a simple classification to a fully axiomatized theory, each providing a different level of formality. Uschold and Gruninger [81] propose four degrees of formality an ontology can provide:

1. *highly informal*: expressed loosely in natural language.
2. *semi-informal*: expressed in a restricted and structured form of natural language.
3. *semi-formal*: expressed in an artificially defined language.
4. *rigorously formal*: precisely defined terms with formal semantics, theorems and proofs of, for example, soundness and completeness.

Ontologies are used in several different communities, and they are a central part in many kinds of applications, such as knowledge portals, information management systems, and semantic Web services [77].

As pointed out in [81], there are three main areas that can benefit from an ontology: communication, interoperability and systems engineering, as depicted in Figure 4.1. Those three areas are of central interest in distributed, service-oriented systems. First, it is all about engineering a system composed of services acting as autonomous, high-level building blocks. Second, those services are required to operate together, often across organizational boundaries. Third, the involved organizations and their people need to communicate in order to develop and deploy inter-operable services. Ultimately, the goal is to compose those services together in order to fulfill a complex workflow. As shown in Chapter 2, this is in particular a requirement of the TAG system.

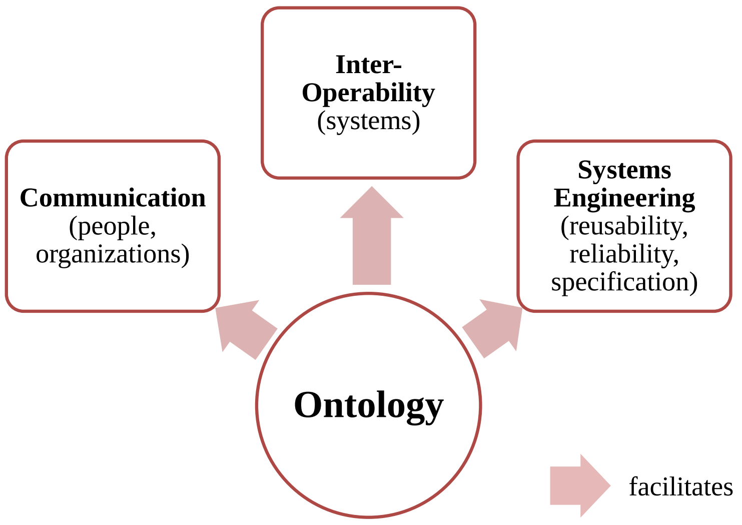


Figure 4.1: Areas for Ontology Uses

In [81], the authors also provide a general methodology for developing an ontology. The required steps are depicted in Figure 4.2. First of all, the purpose and scope, i.e., the *domain* the ontology is aimed at, have to be defined, including a definition of the organization and users supposed to adopt it. The second step is the building of the ontology itself. All the key concepts of the defined domain and their inter-relationships have to be identified, precisely (and unambiguously) defined, and a naming convention has to be adopted. These sub-steps are referred to as *capture*. They are followed by the coding of the ontology in the chosen representation language. If other ontologies already exist for a similar domain, those can either be integrated, or the reasons for building a completely new one should be explained. Design considerations include clarity, coherence, extensibility, minimal ontological commitment (include just enough details to enable a common understanding of the domain of interest, but do not overload) and minimal encoding bias (minimize particular encoding). The third step is the evaluation of the ontology. The formal evaluation consists of applying a reasoner to the ontology, to check for inconsistencies in the semantic definitions of the represented concepts. The more practical evaluation though, i.e., the applicability and usefulness of an ontology for its specified domain, can best be assessed by using it for the sort of application it has been intended for. This is done in this work by deriving an optimization problem based on the concepts defined in the ontology. Finally, good practice and efficient reusability dictate that the ontology should be annotated and documented. It is of particular interest to document special design choices. These steps have been followed in the building of the ontology described in the next sections. The evaluation has been carried out on the TAG use case scenario.

In the subsequent sections, a system and an attribute ontology are proposed and applied to the TAG use case. The aim is to provide a template for describing the building blocks of a distributed, service-oriented system, and relevant attributes in general. By applying these models to the TAG system, the foundations are laid to allow the definition of a concrete service selection optimization problem.

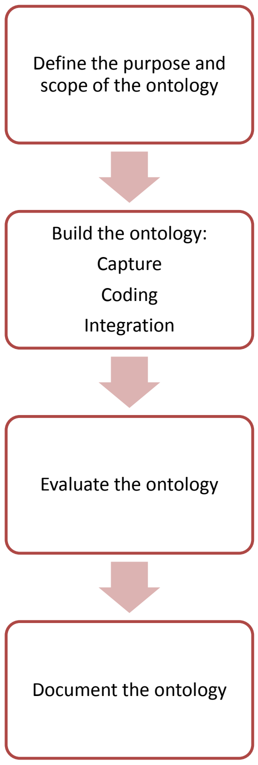


Figure 4.2: Methodology Applied for Building the Ontologies

4.2 System Ontology

The system ontology defines the building blocks of a distributed, service-oriented system, and is in particular applied to the TAG system.

4.2.1 Generic System Ontology

For building the ontology, the methodology outlined in Section 4.1 has been followed.

Domain, Purpose and Scope. The purpose of the ontology is to determine and define the high-level building blocks of a distributed, service-oriented system (in the following, the term *system* refers to distributed, service-oriented system – a definition of the term is part of the ontology). The *domain* of the ontology are systems, independent of their content and application area. It is thus about *how* a system is built, not what it is for and what can be achieved with it. The ontology aims at easing the documentation, extension and operations of such a system. First, by providing a model of a computing system and naming all its components and possible relationships, it can be used as a template for representing and documenting a concrete system. Second, when a developer provides a new piece of software, the ontology helps to integrate it into the existing infrastructure. Finally, knowing the building blocks and their characteristics and properties eases the operations, configuration, and incident detection. Questions being addressed by the ontology include:

- What are the components of a system?
- Which logical components run on which physical components?
- What are the attributes describing each component?
- Which attributes should be included in the service selection process?

Ultimately, the ontology allows identifying the objects and attributes to consider in the service selection optimization process. This will be demonstrated on the example of the TAG system. Users of the ontology include software developers and people ensuring the operations of a system. The ontology is supposed to be maintained by system managers.

Building the Ontology. The ontology building consists of the following three steps.

Integration. The integration has been discussed in Chapter 3, Section 3.3.3.

Capture. The identified *classes*, *object properties*, and *data properties* are summarized in Tables 4.1 and 4.2 and depicted in Figures 4.3 (*inferred* class hierarchy view from Protégé [1], only the relevant classes are shown unfolded) and 4.4 (graphical representation with *OntoGraf*, a built-in representation tool in Protégé).

Coding. The ontology has been implemented using the Web Ontology Language (OWL), using the Protégé toolkit [77]. An overview of the OWL concepts and constructs used to build the ontology is provided in Appendix A.1. The full OWL file is provided in Appendix A.2.

Evaluation. The ontology has been checked for semantic errors using the Protégé plug-in reasoner `HermiT 1.3.4`. The practical evaluation is carried out on the TAG system. The resulting TAG system model is described in Section 4.2.2.

Documentation. There has been no distinction (in terms of classes) made between a *physical* and a *logical* component, because this does not add any relevant information for the domain of discourse and its purpose (for example, logical and physical components can have similar QoS attributes, thus no distinction is required). `Provider` is a defined class, because anything that hosts at least one resource (cardinality restriction) can be considered as a provider in the system. `Deployment` is a defined class, because anything that has the relation `isDeploymentOf` to a resource and a service is necessarily a deployment. Per definition, a deployment can have a single `isDeploymentOf` relation, the range being a resource *and* a service. An individual of the class `Link` has to link (property `links`) at least two individuals, one of the class `Link` to one of the classes `Provider`, `Resource`, or `Deployment`. This is defined so vaguely in order to allow choosing at which level links are defined. For example, if a provider is defined more precisely as a site (as in the TAG context), a link can be defined between two providers, which is a rather generic definition, or between two deployments, which is much more precise, but on the other hand can constitute quite a documentation overhead in a large system. For example, in the

[1]Acknowledgment: This work was conducted using the Protégé resource, which is supported by grant LM007885 from the United States National Library of Medicine.

TAG system links will be defined at the provider level. However, network connections inside a provider can be quite heterogeneous, thus this abstraction removes some precision from the model. A `Link` is also a defined class: any individual in the system that `links` at least two components necessarily belongs to the class `Link`. `AtomicComponent` and `ComposedComponent` are disjoint defined classes. Each individual from the class `SystemComponent` has to have the functional data property `isAtomic` – an `AtomicComponent` has `isAtomic` set to `true`, a `ComposedComponent` has it set to `false`. What a `ComposedComponent` is really composed of is out of the scope here, because it is assumed that only components relevant for the service selection optimization are documented. But the ontology can easily be extended, by stating that each composed component has to be composed of another system component from the same type (i.e., a resource can only be composed of another resource, etc.).

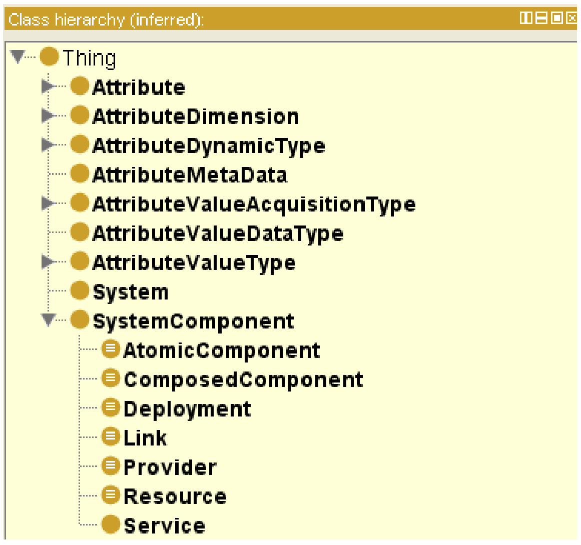


Figure 4.3: Generic System Ontology: Inferred Class Hierarchy

4.2.2 Application: TAG System Components

The components of the TAG system are described in accordance with the ontology defined above. Figure 4.5 shows the derived UML class diagram, and each component is described in the following.

Provider (Site). A *Provider* is also named *Site* in the TAG context. It refers concretely to a Tier of ATLAS hosting at least one deployment of a TAG service. Among the TAG sites, there are both Tier-1 and Tier-2 sites. For information on ATLAS Tiers, the reader is referred to Chapter 2 (Section 2.1) and to the Glossary (Tier). Examples of TAG sites include CERN, TRIUMF (Vancouver, Canada) and DESY (Hamburg, Germany). A concrete provider $P_i, i \in \{1, ..., n_P\}$

Name	**Description**
`Thing`	Root Class in OWL.
`System`	A computing system composed of several components that can act together to provide some defined functionality to users interacting with the system, be they humans or other systems.
`SystemComponent`	Logical or physical building block of a system.
`AtomicComponent` (defined class)	Component that, in the context of the ontology, cannot be further decomposed into smaller components.
`ComposedComponent` (defined class)	Component that, in the context of the ontology, is composed of at least two individuals of the class `AtomicComponent`.
`Provider` (defined class)	(Virtual) organization hosting at least one resource that is part of the system of interest. In the studied context in particular, there is only one virtual organization (ATLAS), and the generically defined *provider* maps to a *site*. Therefore, in the following the term *site* is used, referring to a physical organization hosting at least one resource.
`Resource` (defined class)	Physical or logical entity capable of hosting a service. Examples include web servers, database server or virtual machine. Resources can be nested, e.g., a virtual resource can run on a physical resource.
`Service`	Abstract, self-contained functionality that can be provided as a piece of software or a standalone application and that might be composable with other services.
`Deployment` (defined class)	Instance of a service running on a resource. It is a concrete piece of software that can be invoked over the network.
`Link` (defined class)	Network connection between two physical system components allowing access from component A to component B. It is defined on the component level, because depending on the aimed granularity it can be defined between sites, resources, or deployments.
`Attribute`	Thing describing (characterizing) a `SystemComponent` functionally or non-functionally. The concept of attributes is developed in detail in Section 4.3.

Table 4.1: System Ontology: Classes

Name	**Description**
`consistsOf`	Is the relation between `System` (*domain*) and `SystemComponent` (*range*). A system consists of several components that can in turn be services, resources, etc. The inverse property is `constitutes`.
`hosts`	Is the relationship between a `Provider` (*domain*) and a `Resource` (*range*). An individual has to host at least one resource belonging to the system for qualifying as provider/site. This is a necessary and sufficient condition. The inverse is `isHostedBy`
`hasDeployment`	Is the relationship between `Resource AND Service` (*range*) and `Deployment` (*range*). Each deployment has exactly one inverse property, namely `isDeploymentOf`, to a resource and a service.
`links`	Is the relationship between a `Link` (*domain*) and either a `Provider` or a `Resource` or a `Deployment` (*range*), generally describing a network connection. It is a *symmetric* property, i.e., acting in both directions.
`hasAttribute`	Is the relationship between any `SystemComponent` and an individual of the class `Attribute`. The inverse is `isAttributeOf`.
`hasName`	Data property that assigns a name to a `SystemComponent`.
`hasID`	Data property that assigns a unique ID to a `SystemComponent`.
`isAtomic`	Is a *functional data property* with two possible values (`true, false`) specifying whether a component is atomic or composed. In the latter case it can be decomposed into atomic components. This property defines the disjoint classes `AtomicComponent` and `ComposedComponent`.

Table 4.2: System Ontology: Properties

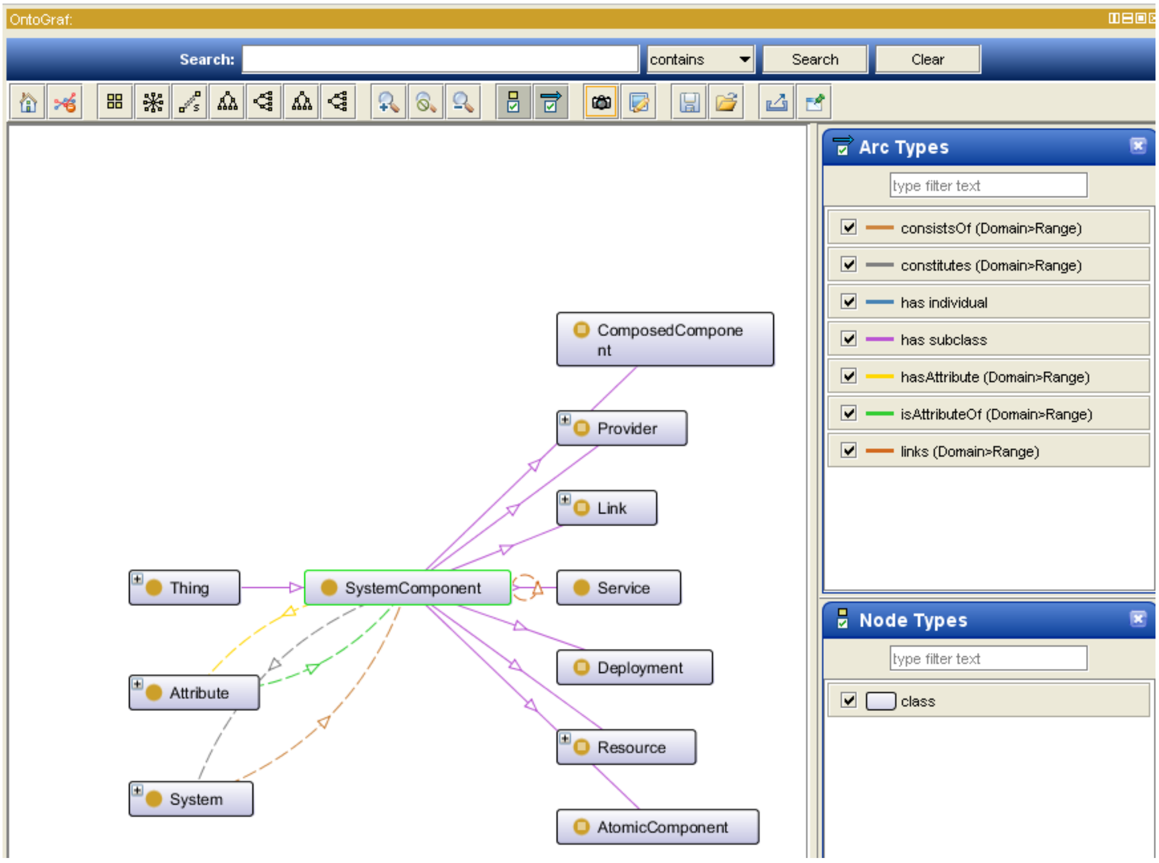


Figure 4.4: Generic System Ontology: OntoGraf Representation

is defined as:

$$P_i = \{id(P_i), [p_{i_1}, ..., p_{i_k}]\} \tag{4.1}$$

where $id(P_i)$ is a function associating a unique identifier, and $[p_{i_1}, ..., p_{i_k}]$ is the vector of k attributes associated to the provider (via the property `hasAttribute` in the ontology). $P := P_1 \cup ... \cup P_{n_P}$ is defined as the union of all providers or sites, where $n_P = |P|$ is the number of providers in the system.

Service. The TAG services are described in Chapter 2 (Section 2.3.4). Formally, a service S_i, with $i \in \{1, ..., n_S\}$, is described using a unique identifier: $S_i = id(S_i)$. $S := S_1 \cup ... \cup S_{n_S}$ is the union of all services and $n_S = |S|$ is the number of services in the considered system.

Resource. In the TAG context, resources include database servers and web servers. Database servers at sites host the TAG database, and web servers host the other TAG services, such as iELSSI and Trigger Decoding. A resource is owned by and hosted at a site (provider). A

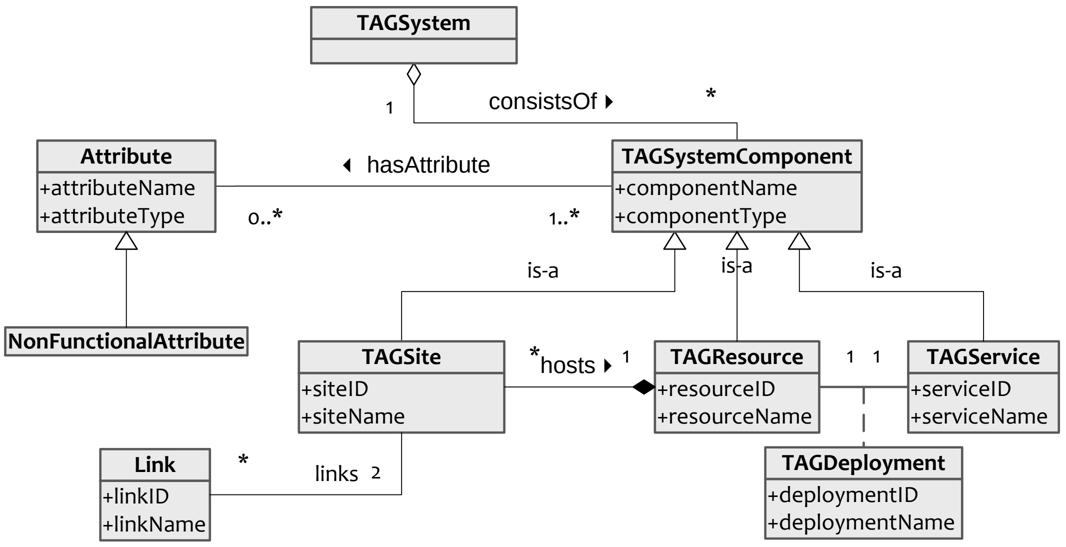


Figure 4.5: TAG System Model (UML Class Diagram)

concrete resource $R_i, i \in \{1, ..., n_R\}$ is defined as:

$$R_i(P_j) = \{id(R_i), P_j, [r_{i_1}, ..., r_{i_l}]\} \tag{4.2}$$

where $id(R_i)$ is a function associating a unique identifier to the resource and $[r_{i_1}, ..., r_{i_l}]$ is the vector of l attributes associated with the resource. As shown in Equation 4.2, the belonging to a provider is part of the resource definition. According to Equation 4.1, this is equivalent to:

$$R_i(P_j) = \{id(R_i), \{id(P_j), [p_{j_1}, ..., p_{j_1}]\}, [r_{i_1}, ..., r_{i_l}]\} \tag{4.3}$$

$R := R_1 \cup ... \cup R_{n_R}$ is defined as the union of all resources, where $n_R = |R|$ is the number of resources in the considered system.

Deployment. A deployment is an instance of a TAG service on a TAG resource. For example, "iELSSI@CERN" is a deployment of the IELSSI service running on a specific web sever at site CERN. Formally, a deployment $D_i(S_j), i \in \{1, ..., n\}$ is defined as:

$$D_i(S_j) = \{id(S_j), \{id(D_i), [d_{i_1}, ..., d_{i_m}]\}\} \tag{4.4}$$

where $id(D_i)$ is a function associating a unique identifier to the deployment and $[d_{i_1}, ..., d_{i_m}]$ is the vector of m attributes associated with the deployment. As suggested in Equation 4.4 the service that a deployment is associated with is part of its definition. $D := D_1 \cup ... \cup D_{n_D}$ is the union of all deployments, where $n_D = |D|$ is the total number of deployments in the considered system.

Link. In the generic model, a link can be defined between any components. In the concrete TAG example, for simplicity and as a first approximation, a link is defined as the network connection between two sites (providers). Defining a link between two resources might be more accurate, but also requires more complex documentation and network monitoring. Formally, a link $L_i, i \in \{1, ..., n\}$ is defined as:

$$L_i(P_j, P_k) = \{id(P_j), id(P_k), [l_{i_1}, ..., l_{i_n}]\} \tag{4.5}$$

where $id(P_j)$ and $id(P_k)$ refer to two sites linked by Link L_i and $[l_{i_1}, ..., l_{i_n}]$ is the vector of n attributes associated with the link. $L := L_1 \cup ... \cup L_{n_L}$ is the union of all links, and $n_L = |L| = |P| \times (|P| - 1)/2$ is the number of links in our system, assuming that no self-links are considered.

Attribute. An attribute of component i is defined as:

$$q_i = \{id(q_i), Dom(q_i), Tgt(q_i)\} \tag{4.6}$$

where $id(q_i)$ is a function associating a unique identifier to the attribute, $Dom(q_i)$ is the *Definition Domain* and $Tgt(q_i)$ is the *Target Domain* of q_i, i.e., the set of all values a_i taken by the attribute.

4.3 Attribute Ontology

As presented in Chapter 3 (Section 3.3.2), many different non-functional attributes are considered in related work on specific service selection problems. Often, a few attributes are given as examples, but it is not clear whether others could be gathered and analyzed, and might have an impact. Additionally, attributes can be very different from each other, due to different units, dimensions, or to the way they are determined. Based on these observations and on the analysis of the related work in the area of QoS attributes in service-oriented systems, an attribute ontology is proposed. Its aim is to provide a high-level framework for classifying QoS attributes, and it thus helps both to identify and to precisely define them.

4.3.1 Generic Attribute Ontology

In the system ontology described in Section 4.2, a class named `Attribute` has been introduced. Individuals from the class `SystemComponent` are related to individuals from `Attribute` via the property `hasAttribute`, that can also be expressed as “characterized by”. The attribute ontology refines the `Attribute` class, both in terms of semantics (what does the attribute express) and syntactics (how is the attribute value constructed).

Domain, Purpose and Scope. The domain of the ontology are non-functional attributes characterizing the components of distributed, service-oriented systems. Its purpose is to provide a framework for classifying such attributes, describing their structure, and specifying whether they are used in the deployment selection optimization process.

Building the Ontology. The ontology building consists of the following three steps.

Integration. The integration has been discussed in Chapter 3, Section 3.3.3.

Capture. The identified classes and properties are represented in Figures 4.6 and 4.7 and described in detail below.

Coding. The attribute ontology has been implemented in Protégé in the same OWL file as the system ontology presented above. The full OWL file is available in Appendix A.2.

Evaluation. In the same way as for the system ontology, the model has been checked with the Protégé built-in reasoner `HermiT 1.3.4` and the applicability is studied on the TAG system, as described in Section 4.3.2.

Documentation. Design considerations are detailed in the description of the classes and properties below.

The following base concepts have been identified as classes in the ontology:

`AttributeMetaData` regroups metadata of attributes used to identify them. For example, an individual from the class `Attribute` should have a name and a unique identifier inside a system, so that it can be unambiguously referred to.

`AttributeValueDataType` is a class regrouping all possible data types that an attribute value can assume. Examples include `integer`, `float`, `boolean`, `string`, etc.

`AttributeValueType` regroups subclasses of types of values that attributes can assume, i.e., absolute or relative. The class `AbsoluteValueType` defines absolute values that can be for example defined and set, measured, or estimated. A `RelativeValueType` is a QoS value that is defined in scales instead of absolute values, such as “low-medium-high”. For example, for the Amazon Elastic Compute Cloud (Amazon EC2) service, instance types are defined in the following categories: *small*, *large*, and *extra large* [4]. Moreover, attributes related to privacy and security can hardly be expressed in absolute values, but they can be rated for instance as low, medium and high. Attributes resulting from user-rankings also usually fall into this category. `RuleValueType` is an attribute type for non-numerical attributes, for example for regulatory attributes expressing the compliance to a certain law. In such a case, the value cannot be a simple number or integer, but can be expressed as a machine-understandable rule.

`AttributeValueUnit` regroups possible units an attribute value can assume. Examples include “bits per second,” “requests per day,” etc.

`AttributeDimension` defines dimensions along which an attribute is computed. Common dimensions include *time* and *size*, but others, as well as *combined* dimensions can be defined. The class `TimeDimension` refers to the dimension of a computed attribute that has a time aspect, i.e., the value is implicitly or explicitly computed per time interval. An example for such an attribute is the *availability*, which is defined as the relative uptime in percent, over a considered time period. A `SizeDimension` refers to the dimension of a computed attribute that has a size aspect, i.e., the value is computed based on size information. An example for such an attribute is the *reliability*, which is defined for a certain number of invocations and is computed by the number of successful invocations divided by the number of all invocations, also denoted in percent. `CombinedDimension` refers to a computed attribute that contains time and size-based information, or any combination of other information. Examples include values for performance, e.g., in tasks per time unit or average data blocks per time unit.

`AttributeValueAcquisitionType` defines the way an attribute value is determined or computed. A `DefinedType` is set and normally not subject to changes. These attributes are usually attached to resources. Examples include CPU count, total RAM available, etc. A `MeasuredType` is a constantly changing value that can be measured at a given point in time. Examples include CPU load and network load as well as free RAM and free disk space. Different techniques can be used for publishing the measured values. For example, *polling* allows gathering attribute values of system components by regularly requesting them. This can be achieved by using either a *push*-based or a *pull*-based notification mechanism. In the push-based case the components publish their attribute values to a central instance, often called *registry*. In the pull-based case the central instance collects the attribute values by querying the components. In case of a *snapshot*-based publishing, the attribute values are collected upon request, usually when the values are needed for the optimization of a request. This technique allows taking into account the state of a component at request time, e.g., in terms of load. In an application scenario, the presented techniques can be combined, depending on which is most appropriate for a given attribute. An `EstimatedType` is a basic value that is estimated instead of measured, for instance by analyzing execution logs. Examples include CPU and network load. Such attribute values can be based on *historical* information, i.e., execution logs are used to derive attribute values, by mining the data. In case of a *prediction*, known values are extrapolated. For example, if the amount of data touched by a given query is known, it can be used to predict the execution time and the resource demand of a deployment for that particular query.

`AttributeDynamicType` includes `StaticType`, `QuasiStaticType`, and `DynamicType`. It specifies whether a considered attribute value is subject to no change (static), very rare changes (quasi static: for example, when a server is upgraded and gets more RAM, this single metric changes, but the resource remains the same, i.e., the values are usually static, but not necessarily throughout the whole lifetime of the component), or frequent changes (dynamic).

The defined properties are the following: `hasValueDataType`, `hasValueType`, `hasDynamicType`, `hasValueAcquisitionType`, `hasDimension`, `hasValueUnit` and `hasMetaData`. The domain of all the properties are individuals of the class `Attribute` (also functional attributes can have such characteristics, although they are not studied here), the ranges are suggested by the respective name of the property. All these properties are *functional*, i.e., each attribute individual can be linked to only one individual of the range class. Intuitively, each attribute has exactly one data type, one value type, one dynamic type, etc. Each attribute individual must be related to exactly one individual via each of these properties, i.e., an attribute must have specified metadata, a specified dimension, acquisition type, etc. If it does not have all of those relationships defined, an attribute does not have enough specification to be included in the deployment selection optimization process.

The following sub-classes of `NonFunctionalAttribute` have been identified, based on the state of the art presented in Chapter 3 (Section 3.3.2):

`PerformanceAttribute`: specifies a measure of the performance of a component, typically a time dimension, e.g., the estimated execution time of a task on a component.

`CostAttribute`: specifies the costs associated with the execution of a task.

`AvailabilityAttribute`: specifies the availability of a component (resource, deployment, link, provider), i.e., its relative uptime.

`ReliabilityAttribute`: provides a measure of how reliable a resource, deployment, link or provider is, usually expressed as the percentage of successful requests compared to all requests.

`ReputationAttribute`: quantifies the reputation of a resource, deployment or provider.

`LoadAttribute`: specifies the current load (at time t) on a resource, deployment or link that influences the execution performance of incoming requests.

`UtilizationAttribute`: specifies the degree of utilization of a system component.

`LatencyAttribute`: specifies the time delay between the submission of a request and its execution on a resource, due for instance to the network.

`BandwidthAttribute`: specifies the available bandwidth, most commonly on a link component.

`ThroughputAttribute`: specifies the available throughput, usually of a network link, as the difference between the theoretically available bandwidth and the current load.

`SecurityAttribute`: specifies a measure for the security level provided (or ensured) by a system component.

`AccessibilityAttribute`: provides a measure for the level of accessibility of a system component, i.e., whether it has access restrictions for example.

`RegulatoryAttribute`: specifies the compliance of a deployment to certain regulatory measures. For instance, data locality can be an issue – data stored in the United States is subject to other data protection rules than data stored in Europe for example.

In a service selection optimization process, often not all QoS attributes are equally important. Weights and priorities can be assigned to them. Weights and priority assignments are characteristics of an optimization problem definition, and are thus not part of the attribute ontology.

4.3.2 Application: TAG System Attributes

Thanks to the central control instance in the TAG system, it is relatively easy to monitor its resources and deployments and collect QoS attributes. For business-oriented workflows, in which services are provided from multiple independent commercial organizations, the deployment usually cannot be monitored, and one has to trust QoS attributes and service level agreements published

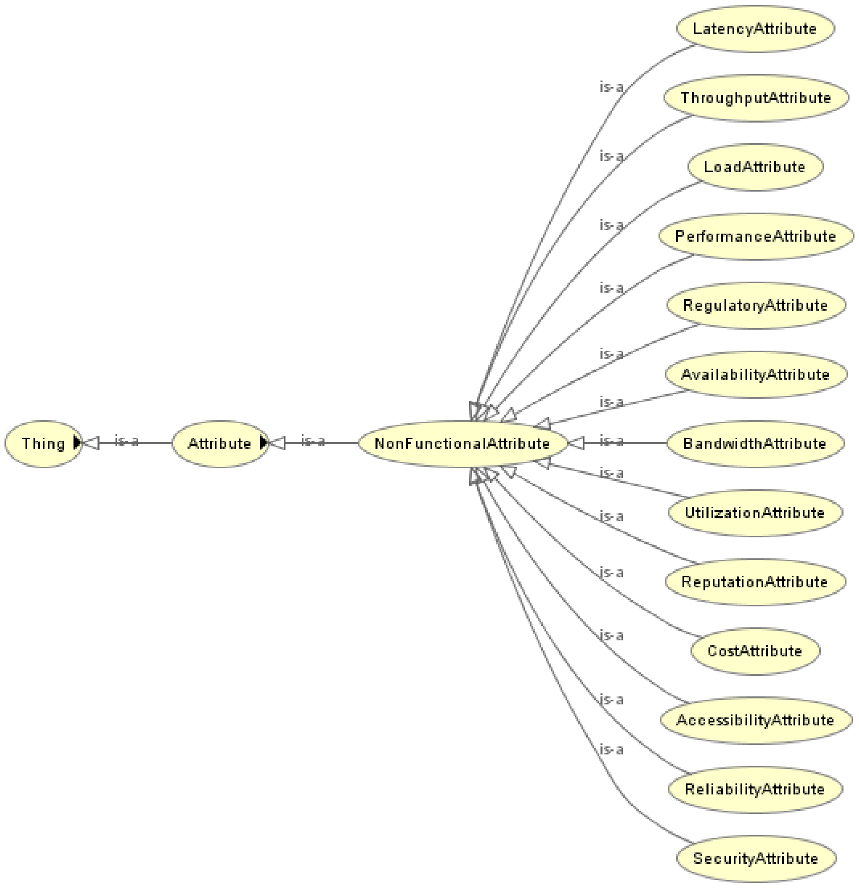


Figure 4.6: Subclasses of `NonFunctionalAttribute`

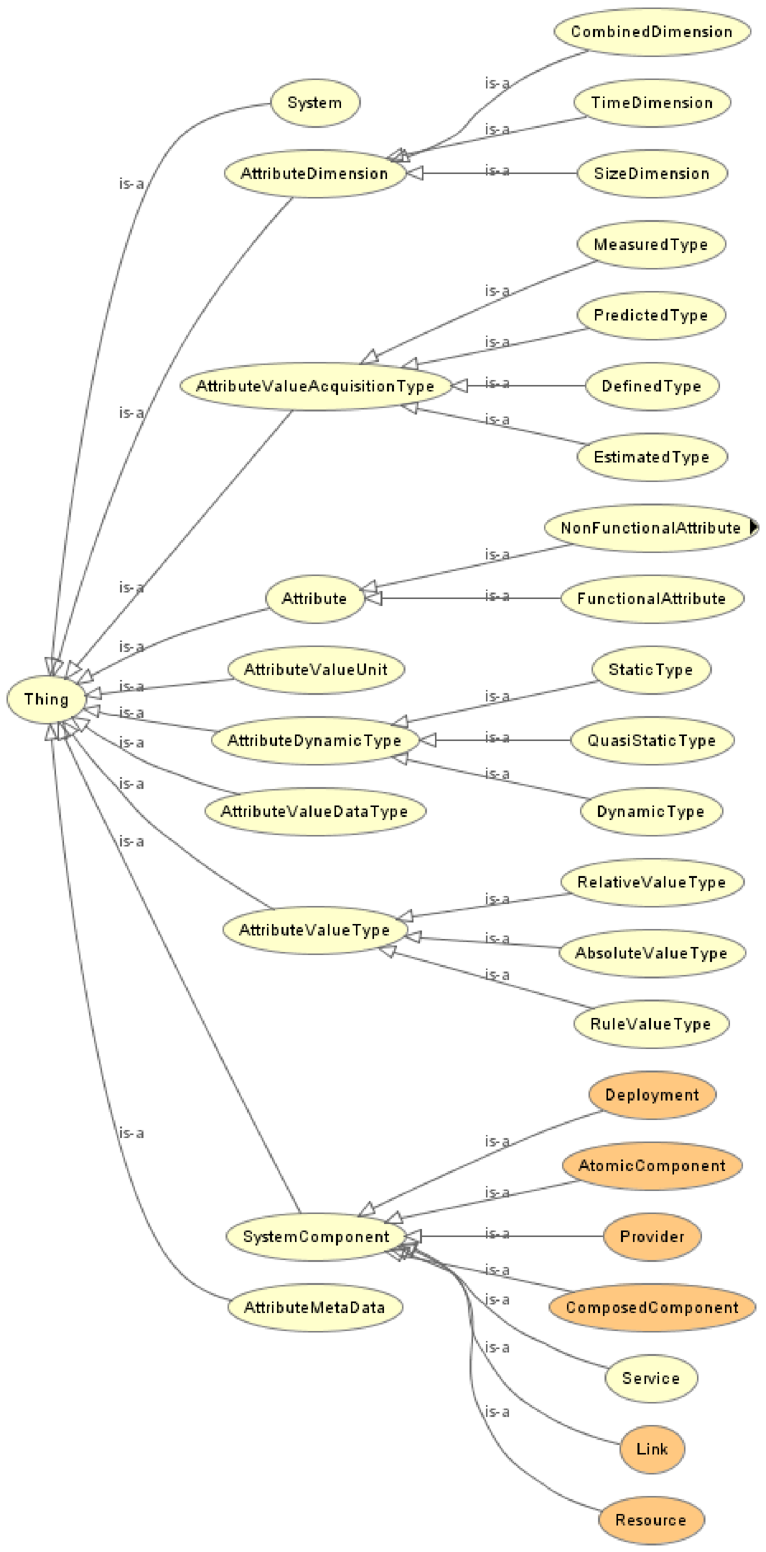


Figure 4.7: Attribute (and System) Ontology: Classes Overview

by the providers. There are several sites in the TAG system, each forming an organization on its own, but all belong to the same Virtual Organization (ATLAS), and configuration issues such as the software version of deployments are centrally managed.

As to *which* attributes to gather, the following aspects are taken into account:

- It has to be decided which attributes are *relevant* for the purpose of a specific optimization, or for other goals that can be enabled by the collection and analysis of QoS attributes. In the TAG use case, two goals have been identified:
  - Deployment Selection Optimization: as described in detail in Chapter 5, a deployment selection optimization problem is defined for TAG workflows, i.e., deployments need to be selected and composed on request in order to form workflows providing the required functionality. The objectives are related to *performance* and *usage*, therefore emphasis is put on attributes describing the performance of deployments and links, as well as the usage of resources.
  - Documentation/General Monitoring: QoS attributes can be interesting to gather and analyze in order to describe the overall service level of a system, even if those attributes are not used for an optimization. For example, it can be required to make a statement regarding the availability of the TAG system, even though the availability metric might not be used in the deployment selection optimization.
- While some attributes can easily be determined (for example the availability of a resource), others might be much more complex to determine properly. One should thus assess which attributes *can* be gathered with a reasonable and justifiable effort.

The following attributes are gathered and taken into account in the TAG system:

Availability defines the relative uptime of a resource or deployment. In the TAG system, it is used for system documentation purposes, and it can appear in a constraint function in the optimization problem. Classification based on the attribute ontology:

```
{AvailabilityAttribute; AttributeMetaData:{availability , $q_{avail}$};
    AttributeValueType:AbsoluteValueType;
    AttributeValueDataType:numeric; AttributeValueUnit:percent;
    AttributeDimension:TimeDimension;
    AttributeValueAcquisitionType:MeasuredType;
    AttributeDynamicType:DynamicType}
```

Reliability defines the success-to-failure rate of a deployment. It is used for information/documentation only, because a degrading reliability is more probable to indicate a structural error or an error in the data than a real deployment failure, unless there is in fact a configuration issue on a deployment or its underlying resource. Therefore, this is an attribute gathered for system monitoring purposes, and it should be watched especially when a new version of a deployment is taken into production. Classification based on the attribute ontology:

{ReliabilityAttribute; AttributeMetaData:{reliability, q_{relia}};
AttributeValueType:AbsoluteValueType;
AttributeValueDataType:numeric; AttributeValueUnit:percent;
AttributeDimension:SizeDimension;
AttributeValueAcquisitionType:MeasuredType;
AttributeDynamicType:DynamicType}

Bandwidth defines the bandwidth of a link in the TAG system, i.e., of a network connection between two TAG sites. Classification based on the attribute ontology:

{BandwidthAttribute; AttributeMetaData:{bandwidth, q_{band}};
AttributeValueType:AbsoluteValueType;
AttributeValueDataType:numeric; AttributeValueUnit:bits per
second; AttributeDimension:CombinedDimension;
AttributeValueAcquisitionType:DefinedType;
AttributeDynamicType:QuasiStaticType}

Latency (Round-Trip-Time) specifies the latency of a link in the TAG system, i.e., of a network connection between two TAG sites. Classification based on the attribute ontology:

{LatencyAttribute; AttributeMetaData:{latency, q_{lat}};
AttributeValueType:AbsoluteValueType;
AttributeValueDataType:numeric;
AttributeValueUnit:milliseconds;
AttributeDimension:TimeDimension;
AttributeValueAcquisitionType:MeasuredType;
AttributeDynamicType:QuasiStaticType}

Load specified the load on a TAG resource. It is a basic attribute included in the performance index (deployment), but it is also gathered separately for documentation/general monitoring purposes. Classification based on the attribute ontology:

{LoadAttribute; AttributeMetaData:{load, q_{load}};
AttributeValueType:AbsoluteValueType;
AttributeValueDataType:numeric; AttributeValueUnit:percent;
AttributeDimension:SizeDimension;
AttributeValueAcquisitionType:MeasuredType;
AttributeDynamicType:DynamicType}

Performance Index (deployment) is an attribute that rates and estimates the performance of a TAG deployment based on historical data and the current load. Classification based on the attribute ontology:

```
{PerformanceAttribute; AttributeMetaData:{perf_ind_D , $q_{perf_D}$ };
    AttributeValueType:AbsoluteValueType;
    AttributeValueDataType:numeric;
    AttributeValueUnit:custom−defined index;
    AttributeDimension:CombinedDimension;
    AttributeValueAcquisitionType:EstimatedType;
    AttributeDynamicType:DynamicType}
```

Performance Index (link) is an attribute that rates and estimates the performance of a TAG link based on the bandwidth, latency and historical data. Classification based on the attribute ontology:

```
{PerformanceAttribute; AttributeMetaData:{perf_ind_L , $q_{perf_L}$ };
    AttributeValueType:AbsoluteValueType;
    AttributeValueDataType:numeric;
    AttributeValueUnit:custom−defined index;
    AttributeDimension:CombinedDimension;
    AttributeValueAcquisitionType:EstimatedType;
    AttributeDynamicType:DynamicType}
```

Usage Index (deployment) rates the degree of utilization of a TAG deployment. This attribute is defined within the scope of a single service, and the sum of the usage indexes of the deployments from one service equals to 1. Classification based on the attribute ontology:

```
{UtilizationAttribute; AttributeMetaData:{usage_ind , $q_{usage}$ };
    AttributeValueType:RelativeValueType;
    AttributeValueDataType:numeric;
    AttributeValueUnit:custom−defined index;
    AttributeDimension:CombinedDimension;
    AttributeValueAcquisitionType:MeasuredType;
    AttributeDynamicType:DynamicType}
```

4.3.3 Attribute Aggregation

As described in the presented ontologies, each deployment has associated QoS attribute values, stored in a registry. However, the focus of the interest for service selection is on the QoS of an entire workflow rather than a single activity. Therefore, the aggregated QoS values have to be determined. To be able to do so, the structure of the workflow has to be known. For example, considering the execution time, it is intuitive that the total execution time of three activities performed one after the other is the sum of the individual execution times. When three activities are executed in parallel, and there is a synchronisation before going on, the overall execution time is equal to the maximum of the three individual execution times. Considering the availability, the aggregation functions are different – it does not make sense to sum availability values for example. Therefore, aggregation functions need to be defined per attribute and workflow structure. The following workflow structures have been identified in TAG workflows (based on the workflow patterns defined by Van der Aalst et al. [83]):

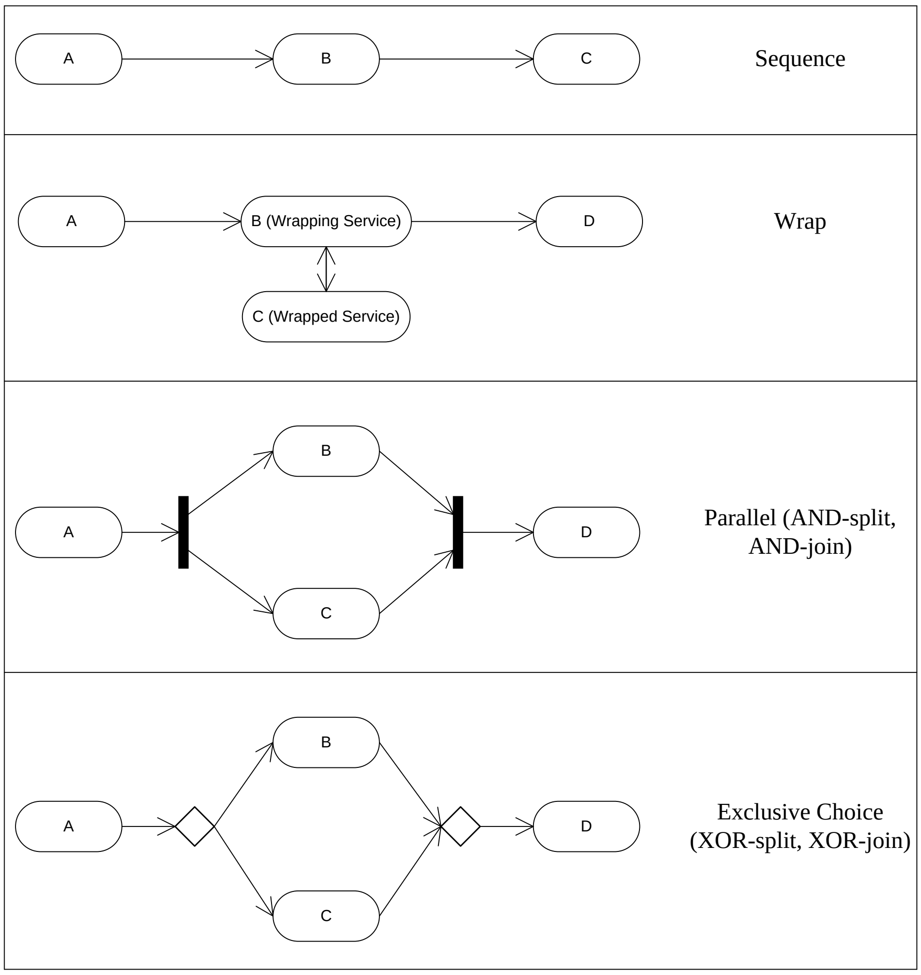

A
B
C
Sequence
A
B (Wrapping Service)
D
C (Wrapped Service)
Wrap
B
A
D
C
Parallel (AND-split, AND-join)
B
A
D
C
Exclusive Choice (XOR-split, XOR-join)

Figure 4.8: Workflow Patterns for Composition

- **Sequence** refers to activities (services/deployments) arranged sequentially, i.e., one is invoked/executed after the other, and the output of one activity can be used as direct input to the next one. In Figure 4.8, activity `A` is executed first, followed by the activities `B`, `C` and `D`, in this order, and there is a control as well as data flow from one activity to the next. This corresponds to *Pattern 1 (Sequence)* presented in [83].
- **Wrap** defines a structure in which a (wrapped) activity is nested into another (wrapping) activity. It is used to model a service that needs to invoke another service to perform a specific

subtask. This can be resolved to a sequence, but as it is a recurring structure in the TAG workflows studied in this thesis, it is defined as a separate structure. In Figure 4.8, activity `B` (*Wrapping Service*) calls activity `C` (*Wrapped Service*) to perform a subtask. The subtask then returns its data and/or control flow to the wrapping service. This can be repeated as many times as needed, depending on the workflow and tasks. The control and data flows finally exit from activity `B` to the next one (`D`). The resulting control/data flow can be represented as a sequence `A-B-C-B-D` in the simplest case, or as a longer sequence if there are several round-trips between the wrapping and the wrapped service, for example `A-B-C-B-C-B-C-B-D` (three calls to the wrapped service). This pattern does not have any analogy in [83].

- **Parallel** defines a structure composed of a parallel split, followed by n branches of activities executed in parallel, and finally a parallel merge or synchronisation. The control flow continues from the synchronisation point only after all parallel branches have been terminated. In Figure 4.8, activities `B` and `C` are executed in parallel. Once they both have finished, activity `D` is executed. This corresponds to a combination of *Pattern 2 (Parallel split)* and *Pattern 3 (Synchronisation)* in [83].

- **Exclusive Choice** is a structure composed of an exclusive choice with n conditional branches, leading to the execution of *one* of these branches, followed by a simple merge. This corresponds to a combination of *Pattern 4 (Exclusive choice)* and *Pattern 5 (Simple merge)* in [83].

It has to be noted that in the context of this work a *loop* in a workflow is unfolded into a sequence, assuming that the number of loops is known. Attributes have to be aggregated over all deployments of a workflow in order to compute the overall value of the attribute, at the workflow level. Each QoS attribute has a specific aggregation function per workflow pattern; typical functions include `sum`, `product`, `min` and `max`. For the attributes introduced in Section 4.3.2, the corresponding aggregation functions are defined in Table 4.3. A similar work has been carried out by Jaeger et al. in [51].

4.4 TASK - TAG Application Service Knowledge Base

This section describes the specific implementation of the so-called TASK (TAG Application Service Knowledge Base) that keeps track of data movements, service deployments, attributes etc.

4.4.1 TASK Schema and Services

The acronym TASK refers to *TAG Application Service Knowledge base*, the TAG management system composed of database schemas, Application Programming Interfaces (APIs), and Web services. Its aim is to allow treating the TAG system as a real distributed system in terms of data and services, and making the distribution invisible to the end users as well as to the TAG services and other services interacting with TAG data. This subsection describes the TASK database schema and related services, as the TAG-specific implementation of the above-mentioned concepts. It thus serves as high-level TASK documentation, for further use. In brief, TASK is composed of three components: the *data catalog*, the *service catalog* and the *logging* component. Very specific details such

Attribute	**Pattern**	**Aggregation Function**
Availability	Sequence	$q_a = \prod_{i=1}^{n} q_i$
	Wrap	$q_a = \prod_{i=1}^{n} q_i$
	Parallel	$q_a = \prod_{i=1}^{n} q_i$
	Choice	$q_a = \min\{x_1, ..., x_n\}$
Reliability	Sequence	$q_a = \prod_{i=1}^{n} q_i$
	Wrap	$q_a = \prod_{i=1}^{n} q_i$
	Parallel	$q_a = \prod_{i=1}^{n} q_i$
	Choice	$q_a = \min\{x_1, ..., x_n\}$
Bandwidth	Sequence	$q_a = \min\{x_1, ..., x_n\}$
	Wrap	$q_a = \min\{x_1, ..., x_n\}$
	Parallel	$q_a = \min\{x_1, ..., x_n\}$
	Choice	$q_a = \min\{x_1, ..., x_n\}$
Latency	Sequence	$q_a = \sum_{i=1}^{n} q_i$
	Wrap	$q_a = \sum_{i=1}^{n} q_i$
	Parallel	$q_a = \max\{x_1, ..., x_n\}$
	Choice	$q_a = \max\{x_1, ..., x_n\}$
Load	Sequence	$q_a = \prod_{i=1}^{n} q_i$
	Wrap	$q_a = \prod_{i=1}^{n} q_i$
	Parallel	$q_a = \prod_{i=1}^{n} q_i$
	Choice	$q_a = \min\{x_1, ..., x_n\}$
Performance Index	Sequence	$q_a = \sum_{i=1}^{n} q_i$
	Wrap	$q_a = \sum_{i=1}^{n} q_i$
	Parallel	$q_a = \max\{x_1, ..., x_n\}$
	Choice	$q_a = \max\{x_1, ..., x_n\}$
Usage Index	Sequence	$q_a = \sum_{i=1}^{n} q_i$
	Wrap	$q_a = \sum_{i=1}^{n} q_i$
	Parallel	$q_a = \sum_{i=1}^{n} q_i$
	Choice	$q_a = \max\{x_1, ..., x_n\}$

Table 4.3: Attribute Aggregation Functions

as database and server names or aliases are omitted here, but made available in dedicated technical TASK documentation. Figure 4.9 gives an overview of the TASK architecture. The core TASK components are the *Central Registry*, the *Logging* and the *Analysis* components. Each component is detailed in the following.

Data Catalog. The TAG data catalog is a set of database tables organized in a data warehouse-like star schema, as shown in Figure 4.10. It is a registry containing information describing the TAG data in terms of provenance and placement. The data catalog tables are populated by the Tier-0 Management System. When a dataset is uploaded to any of the TAG databases, a record of this upload is written to the data catalog. It is thus the source of information about data locality. In detail, the data catalog is composed of the following parts:

Data-related dimensions. The tables `D_RUN`, `D_DATASET`, `AMITAG`, `PASS`, `D_TYPE`, `PROJECT`, `D_COLLECTION` and `D_SUBPORJECT` in Figure 4.10 are dimensions describing the uploaded data. `D_DATASET` contains all the datasets that have ever been uploaded to any TAG database. The AMI tags are normalized in the `AMITAG` table and grouped into passes stored in the `PASS` table. Passes represent a way of grouping the data for displaying for instance in iELSSI. Further means of classification are the type (physics TAGs vs. commissioning TAGs), the project (e.g., "data11") and the subproject (e.g., "data11_7TeV"), stored in the table `D_TYPE`, `PROJECT` and `D_SUBPROJECT`, respectively. `D_RUN` contains a list of all the run numbers for which data are uploaded, with the possibility to set flags for runs that are recommended for analysis. Finally, the relational collections are stored in the `D_COLLECTION` table.

Upload-related dimensions. The tables `D_STATUS_UPLOAD` and `D_STATUS_METADATA` in Figure 4.10 are dimension tables containing information related to the upload of TAGs. All TAG sites are stored in `D_SITE`, and all TAG database schemas in `D_SCHEMA`.

Fact table. The fact table `F_TAGDATA` establishes the relations between all dimensions. There is one row per collection, run, and connection (site/schema) combination. The table contains foreign keys to all dimension tables, and additionally upload statistics, such as the time spent on upload and the time spent on post-processing the data.

Service Catalog. All information related to the components of the TAG system (cf. Section 4.2.2) is stored in the tables belonging to the service catalog, as depicted in Figure 4.11. It is composed of the following parts:

Dimensions. The dimension tables contain information about TAG sites, services, resources, and status in tables `D_SITE`, `D_SERVICE`, `D_RESOURCE` and `D_DEPLOY_STATUS`, respectively.

Fact table. The central table `F_DEPLOYMENT` contains all deployments and links all dimensions together. Conforming to the system model presented in Section 4.2.2, a deployment is an association of a service and a resource (belonging to a site).

Log tables. A few additional tables, named `*_LOGGING` keep track of updates on the fact table and thus allow building an update history.

Logging. The logging schema is composed of one logging table per TAG service being logged, and several tables containing aggregated logging information.

Several systems interact with TASK, as shown in Figure 4.9. The Tier-0 Management System populates the data catalog on upload. It is the only external system writing to TASK. Regarding the documentation of sites and resources, manual input is needed. The active monitoring infrastructure is writing monitoring information into the service catalog.

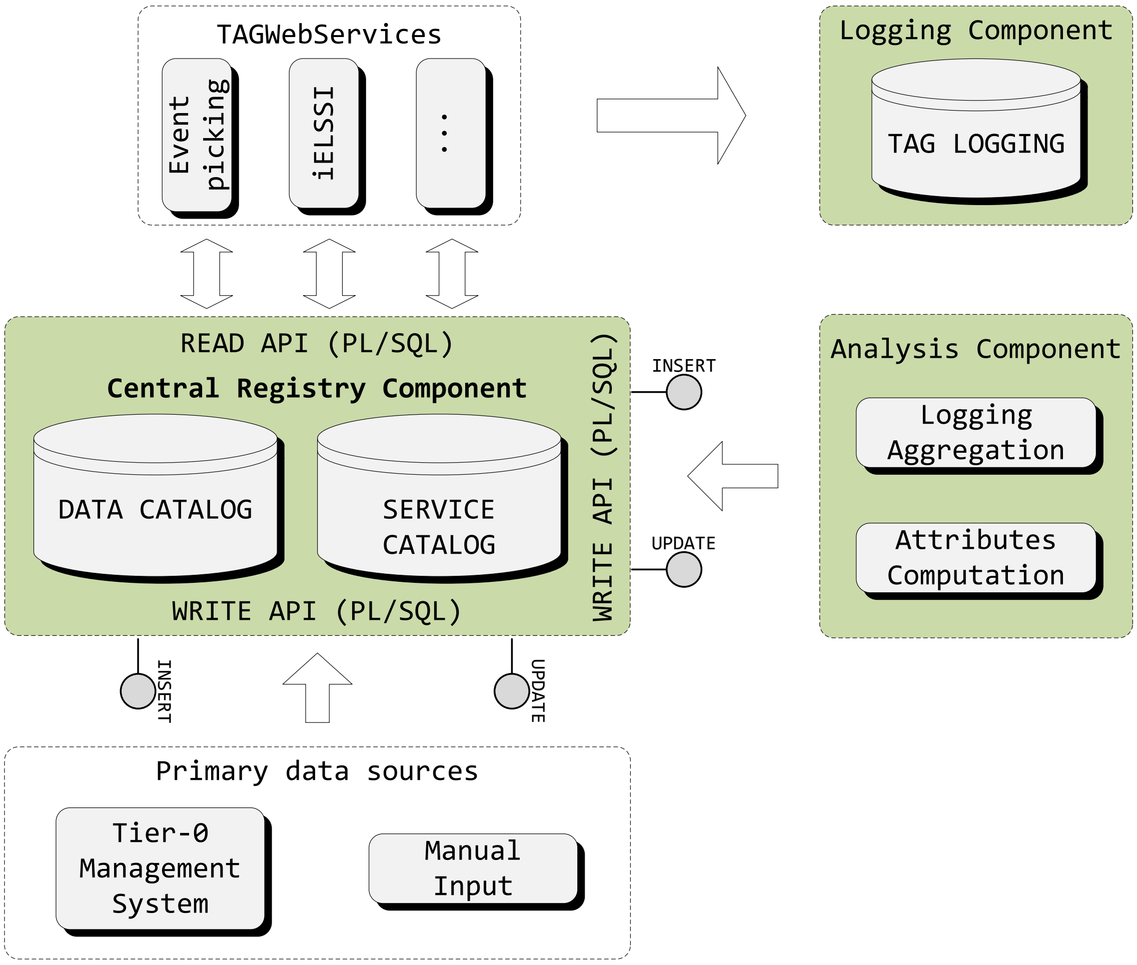


Figure 4.9: TASK Architecture Overview

4.4.2 Gathering System Statistics

TAG system statistics are obtained via active and passive monitoring, where active/passive is defined from the viewpoint of the data-collecting QoS registry ("Central Registry Component" in Figure 4.9). Additionally, basic information about resources (such as total available RAM, CPU count, etc.) can be manually input into the service catalog.

Active monitoring means that tasks executing simple `ping`-like commands are started in reg-

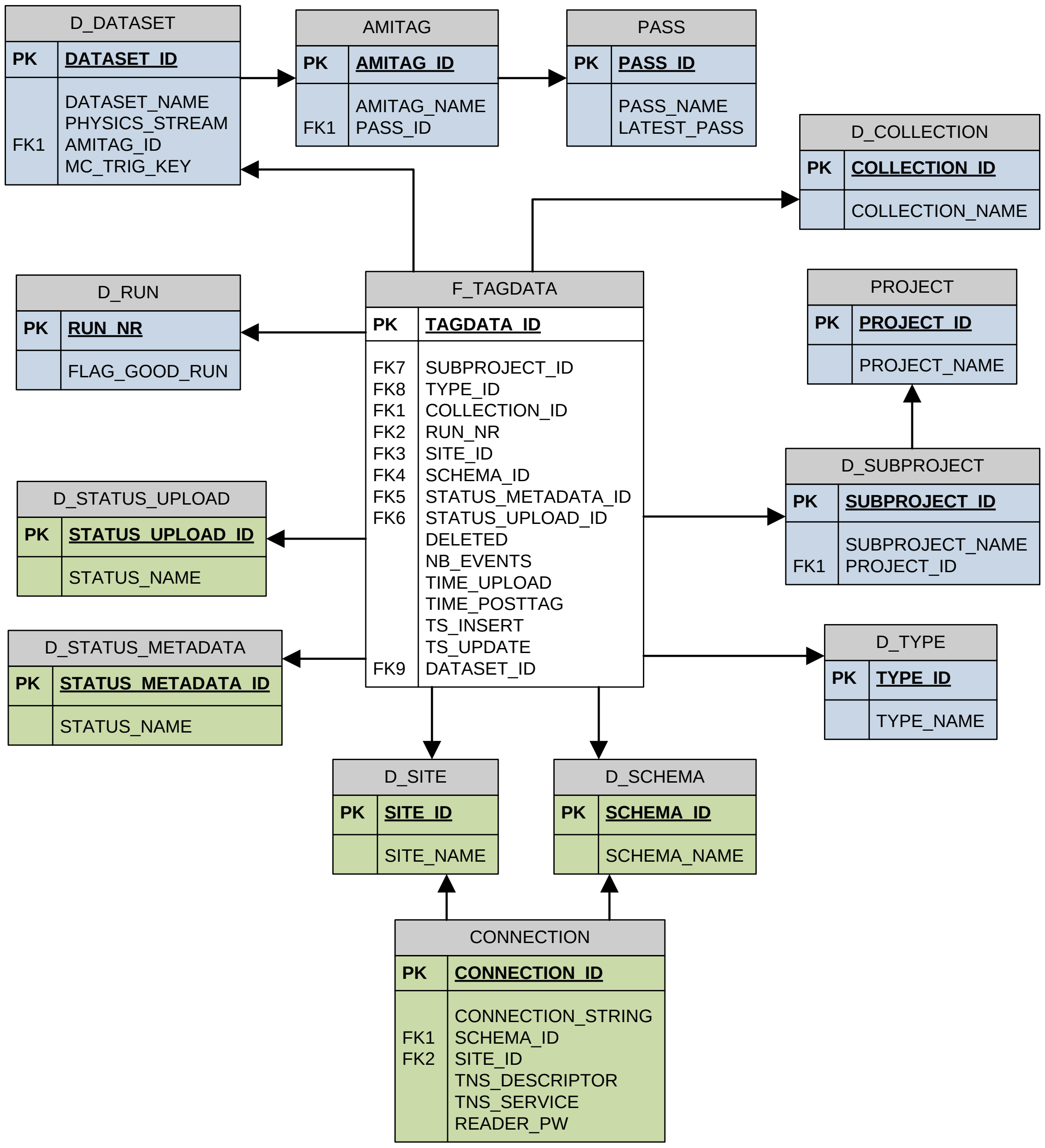


Figure 4.10: TASK: Data Catalog

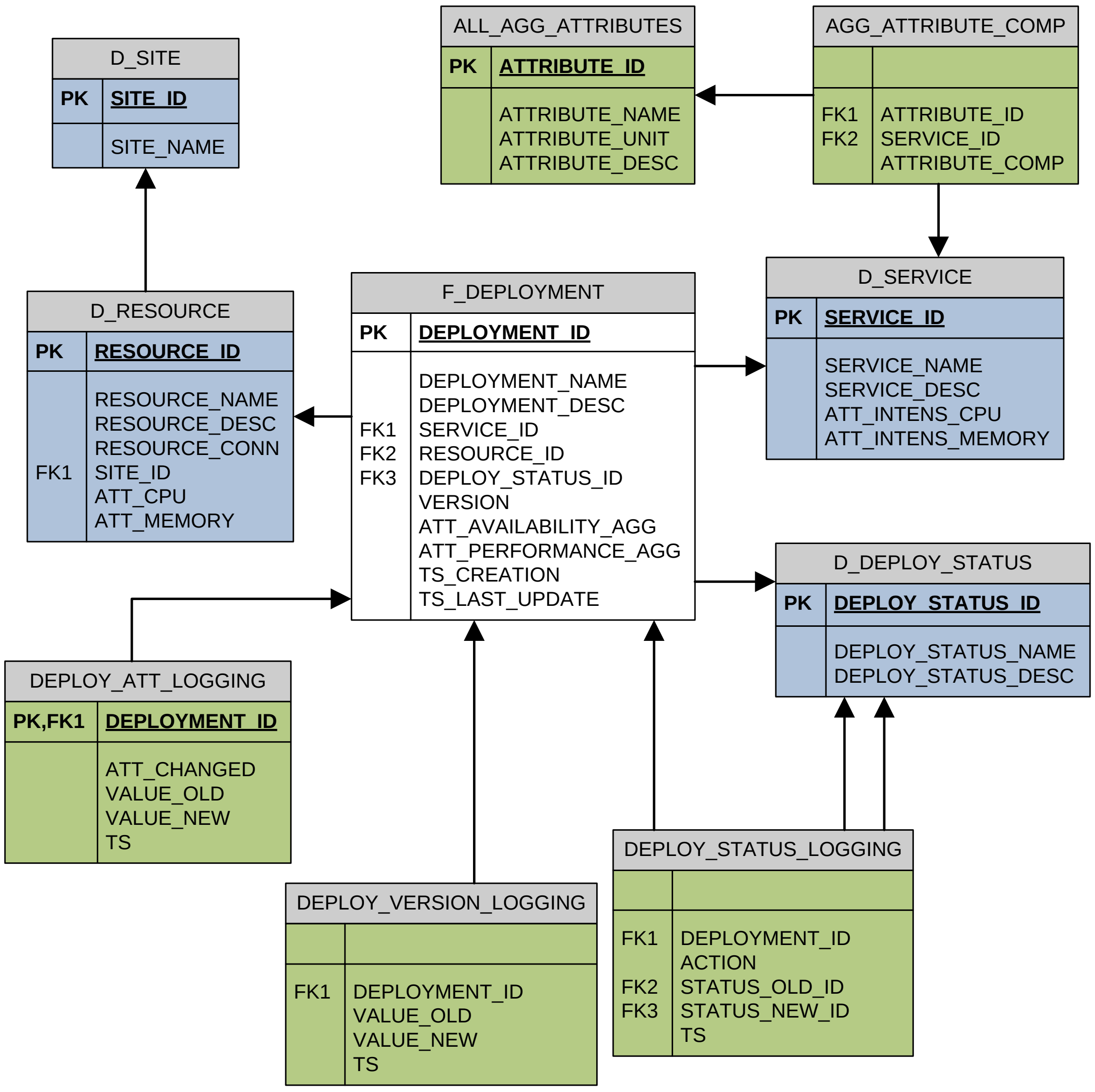


Figure 4.11: TASK: Service Catalog

ular intervals. As soon as a resource or deployment is down, i.e., not reachable, its status is updated in the service catalog and the status change is logged (cf. tables `F_DEPLOYMENT`, `D_DEPLOY_STATUS`, and `DEPLOY_STATUS_LOGGING` in Figure 4.11). This logging information is used for computing the availability of resources and deployments. If all resources hosted by a site are simultaneously down, the whole site can be considered as down.

Passive monitoring refers to the activity of deployments logging information about their executions. Each time a deployment is invoked and executes a request, this activity is logged into a dedicated database schema (cf. "Logging Component" in Figure 4.9), grouped per service. I.e., there is one database table per TAG service and the specification of the deployment is part of the logging information. Example of values logged include the deployment executing the request, the invocation method, the user submitting the request, the requested data (collections, runs), the amount of data touched, the processing time, whether the request/response was successful or not, etc. Statistics about data upload (e.g., number of events uploaded, upload time, etc.) are directly written by the Tier-0 Management System to the data catalog.

Raw logging information collected from both active and passive monitoring is then aggregated (cf. "Analysis Component" in Figure 4.9) in several ways, by running dedicated database and `cron` jobs. For example, in order to determine the top TAG collections and top runs requested by users, the number of requests per collection/run is computed. This allows collecting useful information regarding the usage of the data and services.

4.4.3 Performance and Usage Indexes

The performance indexes of deployments and links are of crucial importance, because they are the main metrics on which QoS decisions in the studied TAG system are based, as will be described in detail in Chapter 5. In the attribute ontology, they are of `AttributeDimension:CombinedDimension` and `AttributeValueAcquisitionType:EstimatedType`. Therefore, their values have to be computed/estimated based on several basic metrics. Performance and load indexes have been broadly studied, for instance in [14, 15]. In [15], the authors define a performance index vector PIV based on CPU, memory and network metrics as follows:

$$PIV = f(I_{CPU}, I_{Memory}, I_{Disk}, I_{Network}) \tag{4.7}$$

where I_x are resource-specific indexes (in this context, the term *resource* refers to CPU, Memory, etc.). Each resource-specific index can be weighted based on the application's requirements. For example, if an incoming request is such that it requires a lot of CPU, I_{CPU} will be weighted higher than the other indexes. Different PIV can then be compared in order to decide to which machine a process should be allocated. In general, such performance indexes are associated to the component type `Resource` as defined in the system ontology, i.e., for instance to a Web server or a database server. However, as suggested in the ontology, the resource and its QoS attributes are "inherited" in the deployment definition (cf. Equation 4.4). Therefore, an aggregated performance index, taking into account both the QoS of the resource and deployment-specific characteristics, can be defined and computed. For example, for the TAG database, statistics on recurring operations executed on all deployments are taken into account and compared. Specifically, the average time spent on extensive, parallelized index creation and statistics gathering for a given amount of data, is a good measure for database performance and it has been verified that this measure correlates with stable metrics such as the number of cores and CPU speed.

Regarding the links, two basic metrics can easily be determined. First, the network bandwidth between two endpoints is a fixed measure. Second, regular checks can be executed to determine the round-trip-time (RTT) between two endpoints. The network throughput, i.e., the actual real available bandwidth (the theoretical bandwidth affected by the actual load) is a metric that is more difficult to determine. However, the analysis of historical data allows deriving time-dependent usage profiles, which in turn can be used to estimate the real network bandwidth at a given point in time.

In general, the following statements apply to performance indexes:

- They are estimations, and therefore approximations.
- There exist different approaches and methods to estimate them.
- Usually, they are computed based on measured actual data and historical data (log analysis).
- There does not exist a single formula, but rather performance indexes of deployments can be defined per service.
- In the context of QoS-aware optimization problems, absolute values for describing performances are not crucial, but relative comparison metrics are needed – performance indexes fulfill this requirement.

Usage indexes in turn can be determined easily. They are defined for deployments of a given service, i.e., performance indexes of two deployments of two different services are not comparable. The usage index $u(D_i(S_j))$ of a deployment D_i belonging to service S_j is defined as the relative number of requests to D_i, relative to the uptime of the deployment:

$$u(D_i(S_j)) = \frac{\text{number of requests to } D_i}{\sum_{x=1}^{n_D} \text{requests to } D_x(S_j)} \cdot \text{availability}_{D_i} \tag{4.8}$$

4.5 Summary

Ontologies specify a shared understanding and vocabulary for a given domain of discourse. In this chapter, ontologies are used to describe the components and non-functional attributes of distributed, service-oriented systems, and in particular of the ATLAS TAG system. The ontologies have been developed using the Protégé toolkit and an OWL/XML syntax. As this is an artificially defined language that allows the specification of exact rules as input to a reasoner, the resulting ontologies are semi-formal according to the classification proposed in [81]. A common and precisely defined vocabulary is important in order to formulate a QoS-aware service selection problem on the system components and attributes. For example, when new components are added that implement the concepts in the ontologies, they can be integrated seamlessly into the optimization process. The inventory of the components as well as their attributes and corresponding values are stored in a central QoS registry. In the TAG application scenario this registry is called TAG Application Service Knowledge Base (TASK). The next chapter describes the use of the QoS attributes in the deployment selection optimization.

Chapter 5

QoS-Aware Service Selection: A Dynamic Multi-Objective Optimization Problem

The distributed TAG system presented in Chapter 4 is dynamic in several aspects. For example, QoS attributes such as the server load are time-dependent. Additionally, optimization objectives, weights, and constraints can change, depending on time and specific non-technical requirements defined by people responsible for the system. A central control instance can *detect* changes in the system, but – depending on the nature of the changes – not always *anticipate* them. Thus, a deployment selection optimization approach has to be able to *react* to changes in the environment. To this end, the various possible changes have to be analyzed, formalized, and taken into account in the concrete optimization problem formulation. Additionally, as in many other real-world optimization problems, and as pointed out in previous chapters, more than one objective can be defined. The deployment selection in the TAG system is thus a dynamic multi-objective optimization problem. Its characteristics and challenges are addressed in this chapter. Based on a classification of dynamics, system and optimization profiles are defined, that are in turn part of the concrete problem formulation.

The sections in this chapter are organized as follows. Section 5.1 analyzes the dynamic aspects in service-oriented systems, starting from the example of the TAG system. In Section 5.2, approaches to detect changes in a problem environment in general and in the TAG system in particular are presented. Based on the derived system and optimization profiles and the system analysis carried out in Chapter 4, the concrete multi-objective optimization problem of the QoS-aware deployment selection is formulated in Section 5.3 as a multi-constrained optimal path problem (MCOP). Characteristics and challenges of multi-objective optimization problems in dynamic environments are outlined in Section 5.4, and the subsequent analysis of the specific problem instance in the TAG system is presented in Section 5.5. Finally, Section 5.6 summarizes the main findings of this chapter.

5.1 Dynamic Aspects of Service-Oriented Systems

Many distributed, service-oriented systems are dynamic in several aspects. The analysis of those dynamics is carried out on the example of the TAG system. It is assumed that similar dynamics appear in other systems having characteristics close to those of the TAG system. The applied methodology also serves as example for analyzing dynamic aspects of other systems.

A system description or blueprint, i.e., an inventory of the active components and their associated attributes and attribute values, is only valid for a given point or period in time, because resources can be down or decommissioned and others added, and QoS attributes change, mainly as a function of the system usage (e.g., the load on a server). Beside these system inherent dynamic factors, there can also be changes in the optimization parameters. These changes are driven by system administration or management decisions. The two categories of dynamic aspects are described in detail in the following. System inherent dynamic factors include:

Components. Sites, resources, links and deployments are not always up and running. For instance, a whole site can decide not to be part of a distributed system anymore, leading to all resources of that site and the associated deployments being decommissioned. They are then no more available as candidate deployments in the selection process. On a temporary scale, resources can be in scheduled or unscheduled downtime, making the associated deployments unavailable for a certain time interval. The existence or absence of components has considerable effects on the decision and solution spaces of the deployment selection optimization problem.

Attributes. Each component has associated QoS attributes subject to frequent changes. For instance, the load of a server at time t can be significantly different from the load at time $t + \Delta t$. Attributes that are computed by averaging over a long time period in general change less frequently. For instance, if a resource has never been down from its commissioning on, its availability will be 100% until it is in its first downtime. As very small variations might be negligible, it is required to introduce levels or ranges of attribute values.

System Usage and User Behavior. Although the system usage can be predicted based on historical logging information (e.g., the average number of requests per day can be used to determine the number of expected requests per day), the way and intensity a system is used can change with time, periodically, slightly, or in an abrupt manner. The system usage has for example an impact on the load of the machines, which in turn influences the performance indexes. Additionally, the popularity of services or use cases can change over time, i.e., the main load on the system can shift from certain abstract services to others.

These system-inherent dynamics are not "controllable," i.e., changes are not accurately predictable and they require a reactive attitute. The optimization process thus has to be able to adapt to those changes, by correctly interpreting their impact on the decision and solution spaces. Changes in optimization parameters on the other hand can be planned. They include the following:

Objective Weights. The weight of one objective relative to the other(s) can be changed, either based on the requirements defined by system managers, or based on system usage patterns. For example, in periods of low system usage, where few incoming requests are expected, it makes sense to put emphasis on optimizing the expected response time for each request, instead of giving advantage to throughput considerations. In periods of high activity instead, system throughput and fair usage considerations are given more weight than the optimization of a single request. These weights have to be defined and set externally.

Prioritization of Use Cases. In real-world systems, it is a realistic scenario to prioritize some use cases over others in a defined time frame. In applications considered in this work, the input to the optimization process is an abstract workflow. There are several distinct abstract workflows, depending on the services they include. For example, in the TAG context, an abstract workflow containing the Extract service can be referred to as *extract use case*. In a period of high data analysis activity (e.g., before conferences) that requires data extraction, the abstract workflows related to the Extract service could be given priority over workflows that do not contain the Extract service. There is thus a need to provide a mechanism for allowing setting such priorities and use them in the optimization process.

Constraints. In the optimization problem defined in Section 5.3, generic constraints are defined, but no concrete one is enabled in the default setting. However, in specific cases it can be required to set constraints. For example, if tasks are defined to be high-priority, constraints can be put on the availability of resources. This reduces the solution space by eliminating infeasible solutions, i.e., those workflows that do not satisfy the aggregated constraints.

Several authors suggested categorizations of dynamic environments [16, 18, 95]. These analyses are done in the context of works dealing with evolutionary optimization. However, most of the suggested categories can be considered independently from the adopted optimization approach. Branke [16] introduces criteria to categorize dynamic environments. He suggests that based on these categories one can derive classes of dynamic environments and design appropriate optimization algorithms. The categorization criteria are the following:

- Frequency of change: measure of how often a change happens. Possible categories range from very rare to continuous.
- Severity of change: measure of how strongly a change impacts the system.
- Predictability of change: defines if changes are random or follow a certain, recurring pattern. If patterns or trends can be determined, it is possible to predict specific changes.
- Cycle length and accuracy: if specific system states are recurring, it is possible to define the length of cycles, i.e., the elapsed time between two (nearly) identical system states.
- Visibility of change: defines whether a change has to be actively detected or is explicitly known to the system.
- Necessity to change representation: this criterion originally refers to the problem encoding in a genetic algorithm, but can be extended to the general case. It specifies whether the change is such that the problem dimension changes, resulting in the necessity to change the problem representation.

- Aspect of change: defines whether the change is affecting the optimization function, the problem instance, or some restrictions (constraints).
- Optimization influence on the environment: in [16], this criterion is named "Evolutionary Algorithm influence on the environment". Here, it is extended to the general case. Solutions produced in an optimization cycle can have direct or indirect impact on the next optimization. For instance, the allocation of a request to a deployment impacts on the load of the underlying resource and thus changes the related QoS attribute.

Table 5.1 details the dynamic aspects of the TAGs as an exemplary system, according to the above categorizations, and provides explanations in the footnotes. The conclusions that can be drawn from this analysis are the following:

1. The changes occurring in the TAG system are diverse regarding several aspects. There is thus not a single solution to address those changes, but several approaches for dealing with the dynamics have to be investigated and optimized.
2. As there is a class of changes with high frequency (changes on attributes), it is useful to introduce lower bounds on changes to be considered, i.e., it is more efficient not to take every very small variation into account, without losing too much solution accuracy.
3. As some changes are predictable and/or recurring cyclically, profiles defining recurring system conditions can be derived.
4. Changes occur on all aspects of the problem, namely on the objective functions, the constraint functions and the problem instance (parameters). These three classes have to be treated separately in order to deduce efficient approaches for each.

The following three "classes of dynamics" are identified and studied separately in the following:

1. Components and attributes: generally unpredictable, non-cyclic, high impact.
2. System usage, objective weights, and prioritization of use cases: generally predictable, cyclic.
3. Constraints: special class, introduces infeasible solutions and involves constraint handling techniques.

	Classification based on [16]					
	Frequency	Severity	Predictability	Cycle	Visibility	Aspect
Components	low	high	partly[a]	no	detected, known[b]	problem instance
Attributes	high	minor to high[c]	no	no	detected	problem instance
System Usage	moderate	minor to high[d]	partly	yes	known	problem instance
Objective Weights	moderate	high	yes[e]	yes	known	optimization function
Prioritization of Use Cases	low	high	yes	yes	known	optimization function
Constraints	low	high	yes	no	known	restrictions

Table 5.1: Qualitative Categorization of Changes in the TAG System

[a]On one hand, unscheduled downtimes for instance are not predictable. On the other hand, when a whole site joins the project, or when a site is decommissioned, this is known well in advance and the change can be prepared.

[b]Cf. previous note.

[c]Depending on the level of change.

[d]Depending on the general system load (far from or close to saturation).

[e]Time profiles can be derived from historical information regarding system usage.

5.2 Detecting and Assessing Changes in the Environment

Changes in the optimization problem and environment have to be detected and assessed in order to be able to react to them appropriately. Depending on the objects affected by changes, different detection methods can be applied. Changes in components and attributes can be captured through active and passive system monitoring, while changes in the optimization definition are known and set externally. In any case, it is necessary to assess the impact a change has on the optimization.

5.2.1 System Monitoring and Profiles

Monitoring can be used to track system inherent dynamics (defined in 5.1) as follows.

Components. When new components are added to or removed from the system, this has a considerable impact on the problem instance. A component can be a site, resource, service or deployment, but in fact only the addition and removal of a deployment have an impact. For instance, if a new site and associated resources are added to the system, but no deployment is hosted there yet, then these resources cannot be considered in a solution anyway. Thus, only the status change of a deployment has to be tracked and marked. In the TAG system, this is flagged in the TASK Service Catalog (cf. Section 4.4). For instance, when a deployment is down, its status is changed from "up" to "down" and a flag is set, indicating that a change has occurred. The first optimization process reading this information resets the flag.

For a given point t in time, the *system status* or *system blueprint* $Sys(t)$ is defined as the union of the available deployments and links: $Sys(t) = D(t) \cup L(t)$, where, as defined in Chapter 4, D is the set of deployments and L is the set of links. According to Equations 4.4 and 4.5, the definition of deployments and links include their attributes, as well as the underlying services, resources and sites.

The following operations are defined and feasible on $Sys(t)$:

- Addition of a deployment D_i between t and $t + \Delta t$: $Sys(t + \Delta t) = Sys(t) \cup D_i$
- Subtraction of a deployment D_i between t and $t + \Delta t$: $Sys(t + \Delta t) = Sys(t) \setminus D_i$

Links are implicitly added and subtracted, as they represent a connection between two deployments. If services, resources or sites are added or removed, this can be mapped to adding or removing deployments attached to the respective component.

Attributes. Monitoring is primarily used to detect changes in attribute values. The monitoring of the TAG system has been described in Chapter 4 (Section 4.4). The latency of detecting a change is defined by the monitoring update intervals. Evidently, there is little chance that a sudden load peak lasting for a few seconds will be detected if the interval of the job monitoring the server load is set to a minute. Additionally, the value for the load is averaged over a time period, resulting in the flattening of peaks. While this better reflects the system status over time, it does not capture with 100% accuracy the system status at time t. There is clearly a trade-off between the accuracy of monitoring information and system load created by the monitoring itself. For the scope of this work, it is safe to assume that the information obtained via the monitoring is up to date and properly describes the system in terms of QoS attributes.

Whenever the value of a QoS attribute changes, a particular flag can be set at the appropriate place in the central registry. This flag is unset as soon as the new value is picked up by a new run of the optimization algorithm. This is an easy and straightforward way to mark changes without having to compare values. A simple check for `Changed = true` thus allows determining if any attribute value has changed since the previous optimization iteration. In the TAG use case, such flags are set and unset in the TASK Service Catalog.

As it is unmanageable to record every small change in an attribute value, levels for the values of the aggregated performance measures are considered. In the terminology of Section 4.2.2, let q be an attribute and $a \in \mathit{Tgt}(q)$ an attribute value. A *level* $(V_a)_i$ of the attribute value a is defined as a range of values of attribute q:

$$(V_a)_i = [a_i, a_{i+1}[= \{x \in \mathbb{R} \mid a_i \leq x < a_{i+1}\} \tag{5.1}$$

Attribute level changes are defined as follows:

$$\begin{aligned} &\text{if } a(t) \in (V_a)_i \text{ and } a(t+\Delta t) < a_i \rightarrow a(t+\Delta t) \in (V_a)_j \text{ for } j < i \\ &\text{if } a(t) \in (V_a)_i \text{ and } a(t+\Delta t) \geq a_{i+1} \rightarrow a(t+\Delta t) \in (V_a)_j \text{ for } j > i \end{aligned} \tag{5.2}$$

Implicitly, there is a function f mapping each attribute value to the level it belongs to. Such a mapping is defined per attribute, because each attribute can take different types and thus requires custom levels. These levels can be defined in the attribute ontology and added to the attribute definition (cf. Section 4.2.2):

$$q_i = \{\mathit{id}(q_i), \mathit{Dom}(q_i), \mathit{Tgt}(q_i), f : \mathit{Tgt}(q_i) \rightarrow V_a := \cup_i (V_a)_i\}. \tag{5.3}$$

System Usage. Variables quantifying the system usage can be derived from monitoring and logging information. For example, the average number of requests per day can be tracked, as well as the distribution of requests during a day. Taking into account these two values only, occurring deviations can be detected. Usage patterns can be derived with different granularity. For example, on a daily basis, hours of high, moderate and low activity can be detected, and request distributions can be analyzed on a weekly basis. These patterns can be used to predict future workload and accommodate the problem parameters. Additionally, the popularity of services can be analyzed from usage logging information. As a consequence, highly popular services or use cases can be given priority over less popular ones. Let $U = u_i, i = 1, ..., n$, be the set of n usage profiles, each indicating a certain usage level.

Based on the above provided definitions, a *System Profile* $SP(t)$ is defined as a vector associating information about deployment status, attributes, and usage at a given point t or period in time:

$$SP(t) := [Sys(t), u(t)] \tag{5.4}$$

where $Sys(t)$ is as defined above, and $u(t) \in U$ is a usage level.

A system profile defines and describes the system status at a given point t in time in terms of available deployments, links, related attributes and usage level. If the system profiles at time t and $t + \Delta t$ differ, then a system-inherent change has occurred in between. The impact of changes is discussed in Section 5.2.3.

5.2.2 Optimization Profiles

Optimization profiles are used to define and track changes in optimization parameters as defined in 5.1. The following aspects are taken into account:

Objective Weights. Objectives are weighted to express which objectives are more important than others to be optimized. When weights can be determined, a multi-objective optimization problem can be transformed into a single-objective problem by combining the objective functions (cf. 5.4). For example, Badr et al. [12] propose to use a weighted-sum approach to reflect user preferences of non-functional features in the combined objective functions. However, in practice it is difficult to properly assign weights. For example, if in a certain period it is more important to optimize a single request than the system load and throughput, should the two objectives be weighted 0.6 to 0.4, 0.7 to 0.3, or any other values? Thumb rules can be applied, but they can be poor approximations and really good solutions might not be considered. As there exist multi-objective approaches that do not require weights to be defined, this feature is used and four simple cases are distinguished as follows for the general case of q objective functions, where w_i and w_j are the weights of objective functions i and j respectively, with $i, j = 1, ..., q$ and $i \neq j$, and $w_i, w_j \in [0, 1], \sum_{n=1}^{q} w_n = 1$.

1. $w_i \succ w_j$: Objective i is given priority over objective j.
2. $w_i \sim w_j$: Objectives i and j are equally important.
3. $w_i \prec w_j$: Objective j is given priority over objective i.
4. $w_i \,?\, w_j$: There is no preference information/knowledge.

In case (1), random values are assigned to w_i and w_j as defined above, with the restriction that the inequality $w_i > w_j$ must be fulfilled. Case (3) is similar, except that the inequality $w_i < w_j$ must be fulfilled. In case (4), no information about objective preferences is available, thus completely random weights are assigned to w_i and w_j. In case (2), the objectives i and j are equally important and the same weight factor is applied to them. In a special scenario, if case (2) applies to all pairs (i, j), then $w_i = \frac{1}{q}$ for all $i = 1, ..., q$. The objective weights vector $o(t)$ is defined as the set of weight relations valid at time t.

The objective weights vector can be used to express prioritization of use cases. For example, in the TAG system one can define two use cases as follows:

1. Interactive queries (iELSSI)
2. Batch jobs (Extract, Skimming, Event Lookup)

In the TAG example, the prioritization of a use case over another means that for workflows of the prioritized use case the deployments should be chosen such that the response time for the whole workflow is minimized, regardless of load-balancing and resource usage strategies. Concretely, this maps to case (1) (i.e., $w_1 \succ w_2$) of the objective weights, assuming that w_1 is the weight of the objective concerned with minimizing the response time, and w_2 the weight of the objective related to load-balancing and throughput. In the general case, a use case prioritization results in an adapted objective weights vector.

Constraints. Regarding constraints, at this level only two cases are distinguished: either the optimization problem is constrained, or it is not. In the former case, concrete constraints have to be defined on any of the available QoS attributes. The presence or absence of constraints has an important impact on the optimization problem, and the constrained case has to be addressed with specific methods, since solutions can be infeasible (i.e., they do not satisfy the constraints) and have to be discarded. $c_i(t), i = 1, ..., m$, is defined as the set of inequality constraints active at time t.

Based on the above definitions, an *optimization profile* $OP(t)$ at time t is defined as:

$$OP(t) := [o(t), c_i(t)], i = 1, ..., m \tag{5.5}$$

In summary, the overall system state at time t is defined by $SP(t)$ and $OP(t)$.

5.2.3 Quantifying System Changes

Whereas the previous two subsections discussed general system dynamics and changes in the optimization parameters, the following considerations take into account a workflow, i.e., they are made on a concrete instance of an optimization problem rather than on the generic one. If several changes occur between two requests that trigger an optimization run, it is necessary to assess those changes in terms of their (potential) impact on the solutions. Therefore, it is beneficial to be able to approximately *quantify* a change. As previously mentioned, any change is marked with a flag and its corresponding timestamp in the central registry. It is thus easy to query all changes that occurred since a certain time t. The proposed method to approximate the degree of change (expressed as a *similarity index*) is based on a component-level classification as follows. The components (deployments, links and their attributes) of a given solution are compared with the system state $Sys(t)$ at the current time t. The comparison is based on the change flags and timestamps of the components. For example, if a new deployment for a service (that is part of the solution) is available, its creation timestamp is newer than the timestamp of the deployment in the last solution. Therefore, this deployment might not be the optimal one anymore. The same applies to links and attributes. The changes of all components and attributes are rated and aggregated to a similarity index. In a simple setup the changes are rated as follows:

- Components are treated equally: the *impact* of a single component C_i, imp_{C_i}, is as listed in Equation 5.6, where n is the number of deployments and m is the number of links in the workflow.
- Changes of attributes of deployments D_i from a service S_j are rated according to the relation of affected to total deployments of the service, as suggested in Equation 5.7. $n_D(S_j)$ is the number of deployments of service j and $x_D(S_j)$ is the number of deployments from service S_j that changed between t and $t + \Delta t$.
- Changes of link attributes are rated according to the Equation 5.8, where x_L is the number of links affected by changes between t and $t + \Delta t$.
- the overall similarity index of all components is si_{total} as listed in Equation 5.9, where n is the number of distinct services in the considered workflow.

$$imp_{C_i} = \frac{1}{n+m}, i = 1, ..., n+m \tag{5.6}$$

$$si_{D(S_j)} = imp_{C_i} \cdot \left(1 - \frac{x_D(S_j)}{n_D(S_j)}\right) \tag{5.7}$$

$$si_L = imp_{C_i} \cdot (m - x_L) \tag{5.8}$$

$$si_{total} = si_L + \sum_{j=1}^{n} si_{D(S_j)} \tag{5.9}$$

This technique is a first attempt to compare two system states and approximately quantify their similarity. The categories derived from the similarity index however have to be defined. An example is provided in Figure 5.1. A similarity index of 1 means that no system change occurred during the observation period. A system change close to 0 suggests a radical change. There are no absolute boundaries between qualitative categories such at slight, moderate and radical change. This can be determined per scenario and optimization approach. In anticipation of the evaluation, in the present scenario a similarity index of approximately 0.5 is the limit beneath which the change is so important that the reuse of knowledge from previous optimization runs has no beneficial influence. However, as suggested by the dashed lines in Figure 5.1, this is a relative boundary. In fact, it does not only depend on the number of changes, but also on the delta of each change. These classifications are however fair approximations for determining an appropriate adaptation of the optimization approach, as will be discussed in Chapters 6 and 7.

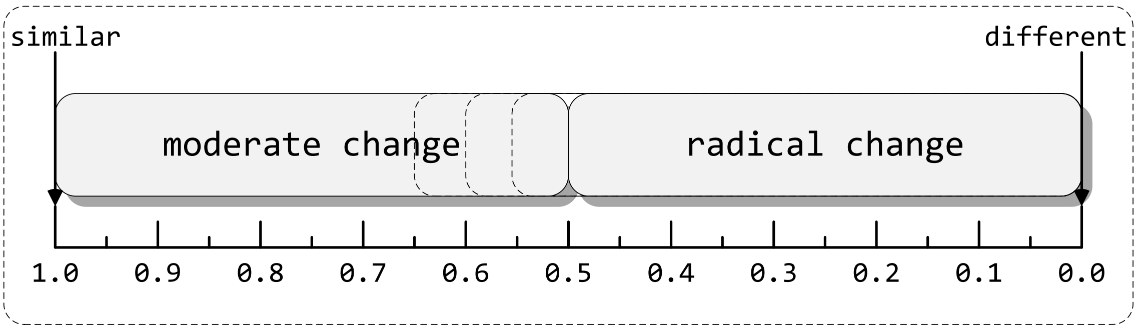


Figure 5.1: Similarity Index and Change Impact

5.3 Concrete Problem Formulation

Putting together the system components and attributes defined in Chapter 4 and the dynamic aspects introduced above, a formal model of the resulting QoS-aware service selection problem is derived. Even though the attributes and QoS indexes are specific to the TAG system, it is a general model that can be applied to other scenarios by replacing the attributes and customizing the objective functions, as needed. Dynamics are included in the form of system and optimization profiles.

5.3.1 Mathematical Model

The QoS-aware service selection problem is modeled as a multi-constrained optimal path problem (MCOP). Yu, Zhang and Lin [104] also proposed such a model for a similar problem setting. Many other authors mapped it to an MMKP (for instance [3, 56]), however, in such a model, links and their associated attributes are not considered, because in an MMKP the items (deployments) from different categories (services) are independent of each other. If links are taken into account, then changing a deployment automatically means changing the incoming and outgoing links. Therefore, the linearity of the objective functions cannot be guaranteed, which in turn excludes techniques relying on the linearity of objective functions and constraints (such as Linear Programming) from the list of possible approaches. It is thus required to develop a more generic model and appropriate solution approaches. An MCOP is an appropriate representation of the QoS-aware service selection problem.

The following building blocks are defined for the problem statement, derived from the system components introduced in Chapter 4 (Section 4.2.2):

- A set $S = \{S_i, i = 1, ..., n_S\}$ of services.
- A set $L_0 = \{L(S_i, S_j), w_{ij}, i = 1, ..., n_S, j = 1, ..., n_S\}$ of abstract links between services, where w_{sij} are weights associated to inter-services links, e.g., latency sensitivity and bandwidth sensitivity.
- A set $D = \{D_i, i = 1, ..., n_D\}$ of deployments. Each deployment $D_i \in D$ has a performance index $perf_{Di}$ (utility value) and a vector of QoS attributes: $[d_{i1}, ..., d_{im}]$ (cf. Equation 4.4).
- A set $L = \{(D_i, D_j), i = 1, ..., n_D, j = 1, ..., n_D\}$ of concrete links between deployments. Each link $L_k \in L$ has a performance index $perf_{Lk}$ (utility value) and a vector of QoS attributes: $[l_{k1}, ..., l_{kn}]$ (cf. Equation 4.5). Because in the concrete TAG model links are defined between sites (providers), not between deployments, a function $s : D \to P$, $P := \cup_i P_i$ (as defined in Section 4.2.2), is defined, that maps a deployment $D_i \in D$ to its site (provider) $P_j \in P$.
- A set $WP = \{wp_i, i = 1, ..., x\}$ of workflow patterns, defined both on abstract and concrete workflows. The patterns are defined in Chapter 4 (Section 4.3.3).
- A function $Agg(wp_i, q_j)$ that associates the right aggregation function (sum, min, product, etc.) to an attribute q_i in pattern wp_i.
- $f_0 : V \to S$ is a service selection map, associating a service S_i to each vertex V_j in a graph representing an abstract workflow. Selecting services implicitly includes the selection of (abstract) links between them.
- $f : V \to D$ is a deployment selection map, associating a deployment D_i to each vertex V_j in a graph representing a concrete workflow. Selecting deployments implicitly includes the selection of (concrete) network links between them.
- v_s and v_d are the virtual source and sink nodes respectively.

An *abstract workflow* W_0 is defined as $W_0 = (V, E, f_0)$, where (V, E) is a directed acyclic graph, and f_0 is a service selection map as defined above. A *concrete workflow* is defined as $W = (V, E, f)$ where (V, E) is a directed acyclic graph, and f is a deployment selection map as defined above. Implicitly, there is a function $g : S_i \to D(S_i)$, associating a list of deployments to each service. This function defines the problem instance, i.e., the available deployments per service.

A concrete workflow is said to be *sensible* for an abstract workflow if the functions f_0 and f are compatible, i.e., the deployment selected for each vertex in W is of the service selected in W_0. In absence of constraints, a concrete workflow W is said to be *feasible* for an abstract workflow W_0 if W is sensible for W_0.

The *workflow performance index* gives an indication of the expected overall performance of the workflow. For each pair (W_0, W), the workflow performance index $p(W_0, W)$ is defined as

$$p(W_0, W) = \sum_{1}^{x} \operatorname*{Agg}_{i,j=1}^{n,m}(\mathit{perf}(D_i), \mathit{perf}(L_j)) \tag{5.10}$$

where $D_i, i = 1, ..., n$, are the deployments (vertexes) in W and $L_j, j = 1, ..., m$, the links (edges) in W and x is the number of workflow patterns in W. The aggregation functions of the performance indexes of deployments and links are detailed in Chapter 4 (Section 4.3.3).

Constraints on QoS attributes can, but do not have to, be defined. After suitable rearrangement of attributes, constraints are defined as:

$$\sum_{j=1}^{x} Agg(wp_j, q_i) \geq Q_i, i = 1, ..., k \tag{5.11}$$
$$\sum_{j=1}^{x} Agg(wp_j, q_i) \leq Q_i, i = k+1, ..., l$$

where $Q_i \in \mathbb{R}$ are user-defined constants, i.e., minimum or maximum requirements, and l is the number of constraints and x is the number of patterns in the considered workflow. Such requirements are defined at the overall workflow level, not at the level of a single vertex or deployment. In presence of constraints, a concrete workflow W is said to be *feasible* for an abstract workflow W_0 if W is sensible for W_0 and such that it satisfies all formulated constraints. For convenience, all ascending attributes (minimum requirements) are assumed to be transformed into descending attributes having maximum requirements. Thus, the constraints can be summarized as:

$$\sum_{j=1}^{x} Agg(wp_j, q_i) \leq Q_i, i = 1, ..., l. \tag{5.12}$$

Finally, a usage index $u(D_i), i = 1, ..., n_D$ is defined at the deployment level. The computation of the usage index is detailed in Chapter 4. This index defines the relative usage of the deployment within the service class it belongs to. This index is thus independent between services.

Figure 5.2 illustrates the above defined concepts of abstract and concrete workflows. From the abstract workflow, it is possible to construct a service candidate graph, as proposed by Yu, Zhang and Lin and depicted in Figure 3.6. The service candidate graph contains all possible paths from the source to the sink. The concrete workflow as shown in Figure 5.2 is one concrete path, i.e., one path from the service candidate graph.

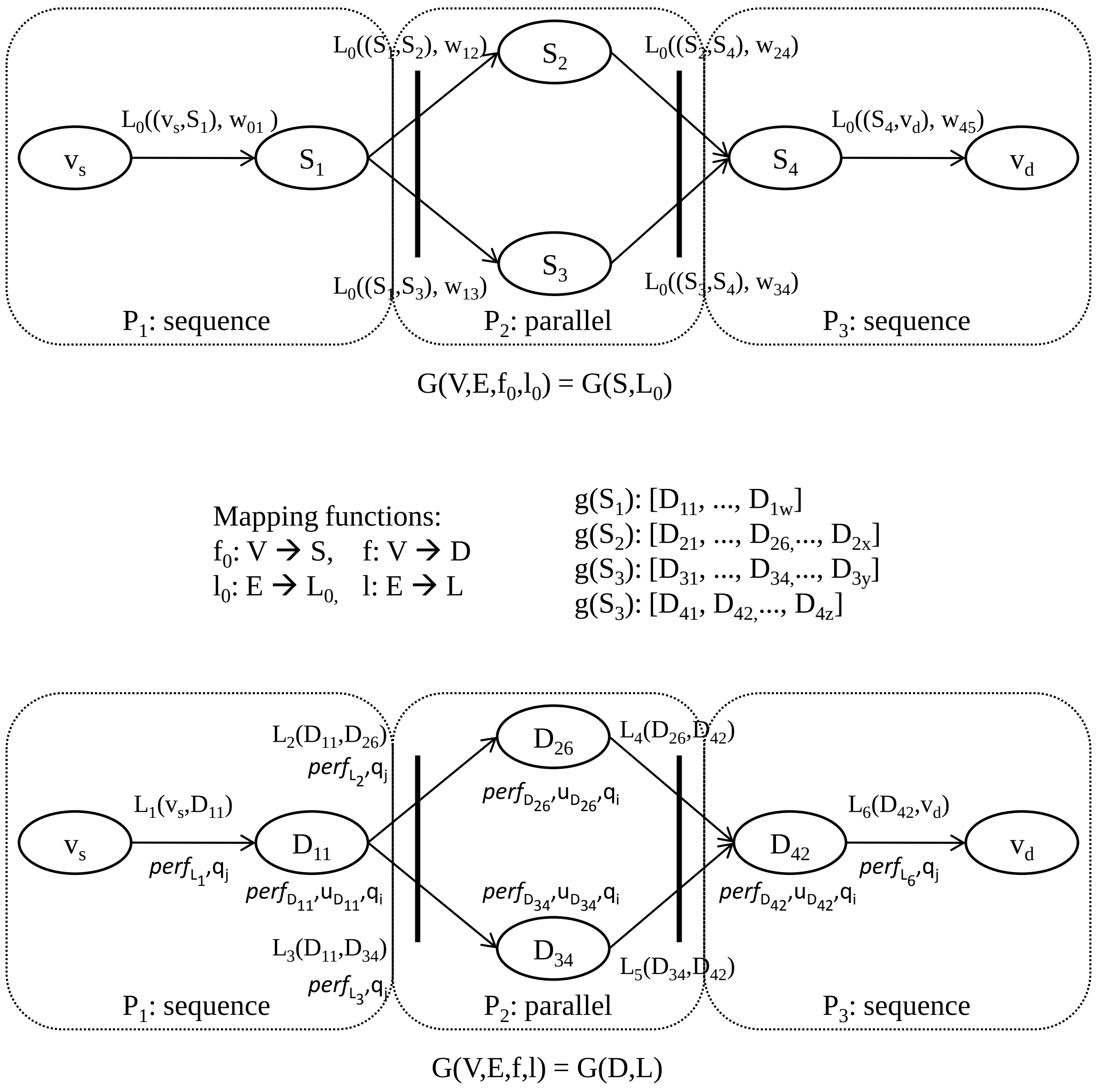


Figure 5.2: Abstract and Concrete Workflow Mapping

5.3.2 Optimization Objectives and Profiles

Many of the QoS-aware service selection problems studied in related work are defined as multi-objective optimization problems (for example [60, 62, 80]). In business scenarios, where the optimization is carried out from the user's perspective only, typical competing objectives are the minimization of the expected execution time of the whole workflow, together with the minimization of overall costs. In the TAG case study, the optimization is approached from the user and the (overall) service provider points of view. That is, one objective is concerned with the user perspective, aiming at minimizing the expected execution time, which can be transformed into maximizing a defined utility value. In the specific problem defined above, this maps to maximizing the workflow performance index. The second objective is concerned with the system perspective and aims at a fair and even resource usage. That is, all deployments of a given service should be used, i.e., all available resources should be accessed, when appropriate. This ensures an overall good system throughput.

Formally, the two considered objectives are:

$$\begin{array}{rll} \max & p(W_0, W) & \\ \min & \sum_{i=1}^{|S|}\sum_{j=1}^{|D_i|} Var(u_j)_i & \\ s.t. & \text{Agg}(q_i) \leq Q_i & i = 0, 1, 2, ..., m \end{array} \tag{5.13}$$

where $p(W_0, W)$ is the workflow performance index of the concrete workflow W implementing the abstract workflow W_0, $|S|$ is the total number of services in W_0, $|D_i|$ is the total number of deployments for service i and $Var(u_j)_i$ is the variance of the usage index u inside a service class i, defined as:

$$Var(u_j) = \sum_{j=1}^{n} (u_j - \mu)^2 \tag{5.14}$$

where $\mu = \frac{\sum_j u_j}{n}$ is the mean and all probabilities are assumed equal to 1, and n is the number of services in the considered service class. Note that the variances can be summed because they are independent through services. According to the duality principle, a minimization problem can be transformed into a maximization problem and vice versa. Equation 5.13 is thus equivalent to:

$$\begin{array}{rll} \max & p(W_0, W) & \\ \max & -\sum_{i=1}^{|S|}\sum_{j=1}^{|D_i|} Var(u_j)_i & \\ s.t. & \text{Agg}(q_i) \leq Q_i & i = 0, 1, 2, ..., m \end{array} \tag{5.15}$$

This problem definition maps to the general form of an MCOP given in Chapter 1, Equation 1.2. A maximization problem can be transformed into a minimization problem, according to the duality principle. In the general form of the MCOP, costs (i.e., the indexes in the presented case) are only defined on the edges. Here, costs on vertexes are also included, thus leading to a special form of an MCOP.

As described throughout this chapter, the studied optimization problem is dynamic. At a given point t in time, exactly one *optimization profile* $OP(t)$ is active. An optimization profile defines:

- the weight ranges of the objectives,
- the prioritization of use cases and
- the constraints.

Taking into account these profiles, the problem can be defined as a dynamic optimization problem depending on $OP(t)$ as follows:

$$\begin{aligned} \max \quad & [p(W_0, W)]_{OP(t)} \\ \max \quad & \left[-\sum_{i=1}^{|S|}\sum_{j=1}^{|D_i|} Var(u_j)_i \right]_{OP(t)} \\ s.t. \quad & [\mathrm{Agg}(q_i) \leq Q_i]_{OP(t)}, \qquad i = 0, 1, 2, ..., m \end{aligned} \tag{5.16}$$

A concrete example of a problem instance taken from the TAG use case is provided in Section 5.5. Although the concrete variables defined above, such as the performance and usage indexes, are taken from the TAG application scenario, the stated problem definition is generic and can be applied to other use cases, by adapting the objective functions to the specific objectives of a problem instance.

5.3.3 Discussion

Specific attention needs to be given to the second objective, i.e., the minimization of the usage variance. Each service has one to many deployments, and each deployment has an associated usage index. The sum of the normalized usage index per service equals to 1, and services are independent of each other. The objective of minimizing the variance of the usage indexes inside each service class aims at distributing the requests between all available deployments over time. It has to be noted that the minimization of the variance is a consideration over time. For a particular optimization iteration, this maps to actually preferring the deployment with the minimal usage index inside its service group. In other words, for each service $S_i \in S$ in W_0, the deployment $D_j \in D$ having $u(D_j) = \min u(D_k)$ for $k = 1, ..., n_D$ is the preferred one. This objective is competing with the objective of minimizing the overall execution time. Thus, depending on the weight assigned to each objective, one or the other objective is given priority. If a deployment has a performance index notably inferior to all others (eventually combined with incoming and outgoing links of poor performance), then, with respect to the first objective, it is not likely to be taken into account in a service composition. The consequence is that its usage index will be lower than the ones of the other deployments of the service. Therefore, in subsequent optimization runs, this deployment will be more and more favored with regards to the second objective. This particular situation arises because the objective of minimizing the usage variance has a direct impact on the subsequent optimizations. In fact, the usage of a particular deployment in a concrete workflow increases its usage index (attribute levels as discussed in Section 5.2 are considered to avoid a constant fluctuation of the index). This behavior is desired for deployments with a competitive performance index (this behavior allows for load-balancing), but it can lead to unwanted behavior for deployments with a very poor performance index. In fact, it may ultimately result in the selection of this deployment in a concrete workflow (which is not desired because of its poor performance index). Therefore, it is required to assume a certain homogeneity in the performance of the deployments. Thus, a performance assessment is carried out in regular intervals or when needed, in order to detect deployments with poor performance compared to the others. If a performance index stays well below the average index of all deployments from a service, it is automatically excluded from the selection. Such a scenario is likely to indicate a recurring error or configuration problem, and thus requires dedicated investigation.

The stated optimization problem is multi-objective and dynamic. In order to adopt an appropriate solution approach, the foundations of multi-objective, dynamic optimization problems in general and this one in particular, have to be understood. In the next sections, MOOP and their characteristics are explained, and the specific problem faced is analyzed.

5.4 Multi-Objective Optimization in Dynamic Environments

The above-described optimization problem has two objectives. All optimization problems having more than one objective are referred to as *Multi-Objective* Optimization Problems, in the following referred to as MOOP. Additionally, the above stated scenario is dynamic in several aspects. The resulting problem is thus a dynamic multi-objective optimization problem. In this section, the characteristics and challenges of such problems are described, thereafter allowing a more profound analysis of the quality-aware TAG-specific optimization problem. This analysis is then presented in Section 5.5.

5.4.1 General Problem Statement

In many real-world optimization problems, there are several optimization objectives. A typical example is the maximization of some utility or performance measure versus the minimization of related costs. These criteria are often conflicting but must be treated simultaneously, which poses specific challenges. For example, the execution of tasks on machines with high performance might be more expensive than on slower resources. Improving the solution with regards to one objective (e.g., maximizing performance) thus automatically worsens the solution with regards to another objective (e.g., minimizing costs). The search for an *optimal* solution is thus a tradeoff between objectives. Such problems exist in various domains, such as economics, engineering, computer science and many more, and there is an important body of research dealing with these MOOP.

The following discussion of MOOP, Pareto-optimal solutions and classical solving methods (Sections 5.4.2 and 5.4.3) is mainly based on the introduction to MOOP provided by Gen and Cheng in [42].

The general form of a MOOP is as follows:

$$\begin{aligned} \max \quad & \{z_1 = f_1(x), z_2 = f_2(x), ..., z_q = f_q(x)\} \\ s.t. \quad & g_i(x) \leq 0 \qquad i = 1, 2, ..., m \end{aligned} \tag{5.17}$$

where $x \in \mathbb{R}^n$ is a vector of n decision variables in the *decision space* S, $z = [z_1, ...z_q] \in \mathbb{R}^q$ is a vector of values of q objective functions evaluating the quality of x in the *objective* or *criterion space* Z, and $g_i(x)$, $i = 1, 2, ..., m$, are inequality constraints. Potential solutions that do not satisfy all constraints and variable bounds are called *infeasible solutions*, all others are referred to as *feasible solutions.* The *feasible region* is defined as the set of all feasible solutions. In MOOP, the objective functions spawn a multi-dimensional objective space Z. They map an n-dimensional solution vector into a q-dimensional objective vector. Figure 5.3 illustrates the decision and objective or criterion spaces for a general MOOP.

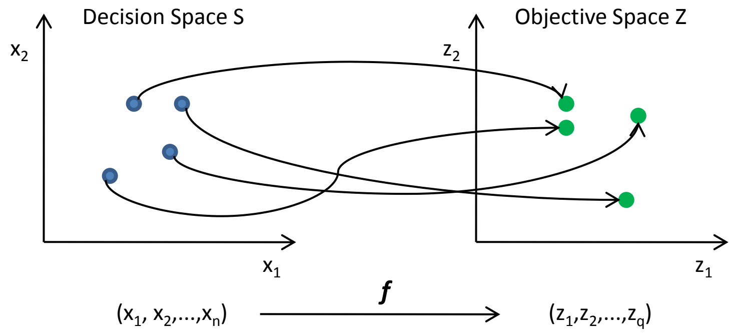


Figure 5.3: Multi-Objective Optimization Problem: Decision and Objective Space

5.4.2 Pareto-Optimal Solutions

As opposed to single-objective optimization problems, in MOOP there generally does not exist a single *best* or *optimal* solution superior to all other (feasible) solutions. Instead, there is a trade-off between conflicting objective functions. A solution can be the optimal one for one objective function, but the worst regarding another objective function, to state the extreme case. As a result, in MOOP one attempts to find a *set* of solutions that cannot be compared with each other without having additional information, for example about weights between the objectives. This set is composed of those solutions for which the improvement regarding one objective automatically leads to a worsening of at least one of the other objectives. These solutions are called *non-dominated* or *Pareto optimal*. The set of Pareto optimal solutions is referred to as the *Pareto front*.

Definition 1. *A given point $z^0 \in Z$ is* ***non-dominated*** *if and only if there does not exist another point $z \in Z$ such that (for the maximization case),*

$$\begin{aligned} z_k &> z_k^0, && \text{for some } k \in 1,2,...,q \\ z_l &\geq z_l^0, && \text{for all } l \neq k \end{aligned}$$

In other words, a point is non-dominated if there is no other solution better with regards to one objective and better or equally good with regards to all other objectives. This definition can be extended as follows. A solution $z^0 \in Z$ is ***strongly non-dominated*** *by a solution $z \in Z$ if z^0 is better regarding all objectives, and* ***weakly non-dominated*** *if z^0 and z are equally good for at least one objective.*

Considering the problem from the decision space, a point x in this space is *efficient* as follows:

Definition 2. *A given point $x^0 \in S$ is* ***efficient*** *if and only if there does not exist another point $x \in S$ such that (for the maximization case),*

$$\begin{aligned} f_k(x) &> f_k(x^0), && \text{for some } k \in 1,2,...,q \\ f_l(x) &\geq f_l(x^0), && \text{for all } l \neq k \end{aligned}$$

In other words, $x \in S$ is efficient if and only if its image $z \in Z$ is a non-dominated point.

As a MOOP solver returns a set of solutions instead of a single solution, one particular solution has to be selected by the decision maker as the final one. This is usually achieved by setting preferences, for instance by weighting the objective functions, thus giving some objectives priority over others and preferring solutions that are better for the priority objectives. A *preference* thus allows ordering the non-dominated solutions according to subjective value judgments. The final *best* solution found with this ordering is called the *best-compromised solution.* Binary relations allow representing preferences. A *binary relation* is a set of ordered pairs that allows defining the preference relation between two solutions. For a given pair of solutions u and v, the preference between them can be expressed by one and only one of the following relations:

- u is better than or *preferred* to v: $u \succ v$.
- u is worse or *less preferred* than v: $u \prec v$.
- u is equivalent or *equally preferred* to v: $u \sim v$.
- The preference relation between u and v is *indefinite*: $u?v$.

From these binary relations, the following sets of relations between solutions can be defined:

- $\{\succ\}$ is the set of preferred relations.
- $\{\prec\}$ is the set of less preferred relations.
- $\{\sim\}$ is the set of equally preferred relations.
- $\{?\}$ is the set of indefinite preference relations.

In many real-life problems, it is nearly impossible to determine the entire Pareto-optimal set, because of the problem size. However, a subset of the Pareto-optimal set can be found. This set is referred to as *best-known Pareto set.* According to Zitzler, Deb and Thiele [109], the ultimate resulting goals of a multi-objective optimization are the following:

- The obtained best-known Pareto set should approximate the Pareto-optimal set as close as possible.
- Solutions in the best-known Pareto set should be uniformly distributed and diverse. This allows presenting a real picture of the trade-off to the decision maker.
- The solutions in the best-known Pareto set should cover a wide range of solutions, i.e., solutions of the extreme ends of the criterion space should be considered.

These aspects should be investigated when evaluating a given MOOP approach.

5.4.3 Classical Solving Methods

In this section, exemplary basic approaches to solve MOOP are outlined. The key concepts behind those methods are important because they can be incorporated into evolutionary approaches.

Miettinen [65] suggests the following classification of methods for solving MOOP:

- No-preference methods: these methods do not assume any information about preferences such as weights of objectives.
- A posteriori methods: after having produced a Pareto-optimal solution set, the decision maker can select the most preferred solution.
- A priori methods: preferences are defined in advance, reflecting the expectations of the decision maker.
- Interactive methods: these approaches include the decision maker in the solution generating process.

Exemplary basic methods, as suggested by Gen and Cheng [42] are described in the following.

Weighted-Sum Approach. Weights are assigned to each objective function. This then allows transforming the MOOP into a single-objective optimization problem as follows:

$$\begin{aligned} \max \quad & z(x) = \sum_{n=1}^{q} w_k f_k(x) \\ s.t. \quad & x \in S \end{aligned} \tag{5.18}$$

where S is the solution space. The weights w_k represent the preferences of the objectives. If all the weights are positive, the optimal solution is a non-dominated solution [42]. The numerical ordering results in preferred, less preferred and equally preferred solutions, and $\{?\} = \emptyset$. This approach classifies as an a priori method.

Utility Function Approach. A utility function allows representing a preference structure. Every point of the criterion space is mapped to a real number. The greater this number, the more preferred is the corresponding point in the criterion space. In practice, it is however difficult if not impossible to define an appropriate utility function. In this method again, $\{?\} = \emptyset$ because a real number value is assigned to each solution. This approach classifies as an a posteriori method.

Compromise Approach. This method seeks to evaluate the distance between every solution in the Pareto-optimal set and the theoretical *ideal point.*

Definition 3. *The* ***ideal point*** $z^* = (z_1^*, z_2^*, ..., z_q^*)$ *is the point in the criterion space where* $z_k^* = \sup\{f_k(x) | x \in S\}, k = 1, 2, ..., q$. *It is usually not attainable.*

It defines the *regret* of obtaining solution z instead of the ideal solution z^* by the following distance function:

$$r(z) = \|z - z^*\| \tag{5.19}$$

where $\|z - z^*\|$ is the distance between z and z^* according to a norm that has to be specified for a given problem. The resulting regret function associates a real number to every solution, leading again to $\{?\} = \emptyset$. This approach classifies as an a posteriori method.

Lexicographic Ordering Approach. The k objective functions are ordered so that the k^{th} objective is clearly more important than the $(k+1)^{th}$ objective. A given point z^1 is then preferred to z^2 if and only if $z_1^1 > z_1^2$ or there is some $r \in \{1, 2, ..., q\}$ so that $z_r^1 > z_r^2$ and $z_i^1 = z_i^2$ for $i = 1, 2, ..., r-1$. In this ordering approach again, $\{?\} = \emptyset$. This approach classifies as an a priori method.

Pareto Approach. This approach does not make any assumptions on preferences among objectives. It is thus a method addressing problems where the set $\{?\}$ is not empty. The sets of relations are defined as follows:

$$\begin{aligned} \{\succ\} &= \{(z^1, z^2) \in Z\text{x}Z | z^1 \geq z^2\} \\ \{\sim\} &= \{(z, z) \in Z\text{x}Z | z \in Z\} \\ \{?\} &= \{(z^1, z^2) \in Z\text{x}Z | \text{ neither } z^1 \geq z^2 \text{ nor } z^1 \leq z^2\} \end{aligned} \tag{5.20}$$

This approach classifies as a no-preference method.

5.4.4 Dealing with Dynamic Environments

A dynamic MOOP is a MOOP that changes with time. These changes can occur at any of the following levels or any combination of them [34]:

1. Objective functions
2. Constraint functions
3. Problem parameters

More specifically, based on the definitions of a general MOOP provided in Section 5.4.1, a dynamic MOOP can be defined as follows [21]:

$$\begin{aligned} \max \quad & \{z_1 = f_1(x, t), z_2 = f_2(x, t), ..., z_q = f_q(x, t)\} \\ s.t. \quad & g_i(x, t) \leq 0 \qquad i = 1, 2, ..., m \end{aligned} \tag{5.21}$$

where t is the time variable. The time-dependent solution sets are defined as follows [40]:

Definition 4. *$\mathcal{S}_\mathcal{P}(t)$ is the set of Pareto-optimal solutions at time t in the decision space. $\mathcal{F}_\mathcal{P}(t)$ is the set of Pareto-optimal solutions at time t in the objective space.*

The ideal point (as defined in Definition 3) is also time-dependent:

Definition 5. *The **ideal point** $z^*(t) = (z_1^*(t), z_2^*(t), ..., z_q^*(t))$ is the point in the criterion space where $z_k^*(t) = sup\{f_k(x, t) | x \in S\}, k = 1, 2, ..., q$.*

Farina, Deb and Amato [40] propose a basic classification of dynamic MOOP based on Definition 4:

1. The optimal decision variables $\mathcal{S}_\mathcal{P}$ change, whereas the optimal objective values $\mathcal{F}_\mathcal{P}$ do not change.

2. Both $\mathcal{S}_{\mathcal{P}}$ and $\mathcal{F}_{\mathcal{P}}$ change.

3. $\mathcal{S}_{\mathcal{P}}$ does not change, whereas $\mathcal{F}_{\mathcal{P}}$ changes.

4. Both $\mathcal{S}_{\mathcal{P}}$ and $\mathcal{F}_{\mathcal{P}}$ do not change, although the problem can change.

Each type of changes requires a special handling in the algorithm. Other possible dynamics are changes in the decision maker's preferences as well as new or removed objectives and constraint functions.

Deb, Rao and Karthik [34] point out that there are two basic ways of addressing dynamic optimization problems. One approach is to run the optimization off-line for some realistic scenarios of the dynamic problem faced. This is suitable for large problems that are computationally expensive, making an online approach not scalable or inefficient. It is however incapable of automatically reacting to newly appearing changes, and requires that the type and extent of the changes in the system are known beforehand. The other approach is to run the optimization algorithm online, when required. Doing this, one assumes that the problem is stationary during the optimization procedure. The shorter the optimization procedure, the safer is this assumption. In the next optimization iteration, a new problem is considered, taking into account all the changes since the previous iteration. The authors also describe an important trade-off encountered in dynamic online optimization. The following assumptions are made and values are defined:

- The change in the optimization problem is gradual in t.
- One optimization iteration requires a finite time G.
- $\mathcal{T}_T$ iterations are allowed or needed to reach an optimal or near-optimal solution.
- The problem does not change within a time interval t_T. $G\mathcal{T}_T$ is the initial time taken by the algorithm to find a solution under changed conditions, and $G\mathcal{T}_T < t_T$.
- $\alpha = G\mathcal{T}_T/t_T$ is a small value, such that $(1-\alpha)t_T$ time is spent on using a specific solution after its computation.

Figure 5.4 [34] illustrates the problem setting. The value to be decided on is the value of t_T. If t_T has a large value, then the system is assumed to be stable in a longer time interval, which allows a larger number of iterations $\mathcal{T}_T$. After a larger time interval, the changes can be expected to have a greater impact than after a shorter interval. But as a higher number of iterations is allowed, there may be enough iterations to reach the new trade-off optimal solutions. On the other hand, if t_T has a smaller value, changes are more frequent and generally less impacting, but fewer iterations can be carried out. With too few iterations, no good-quality new solution may be found. There is thus a lower bound on t_T that needs to be defined. This depends on the nature of the underlying dynamic optimization problem as well as on the chosen algorithm.

Furthermore, it can happen that new requests are arriving while others are still being executed. This is an issue in dynamic problems, because some QoS values required for the optimization might not be up to date. An example is the usage index: the information that a specific deployment has been used might not yet have been written to the central registry and therefore, the new optimization runs is starting with a deprecated usage index value. This issue is partly addressed by introducing attribute value levels (cf. Section 5.2). However, if many requests are suddenly issued at the same time, this becomes a serious consideration.

Camara, Ortega and de Toro [21] point out that dynamic optimization procedures require specific evaluation criteria. Specifically, three measures should be considered when evaluating an algorithm designed for dynamic MOOP: the *accuracy* assessing the quality of the solutions found, the *stability* expressing the effect of changes on the algorithm accuracy, and the *reaction capability* measuring the capability of an approach to react and adapt to changes. These evaluation criteria are discussed in more detail in Chapter 7.

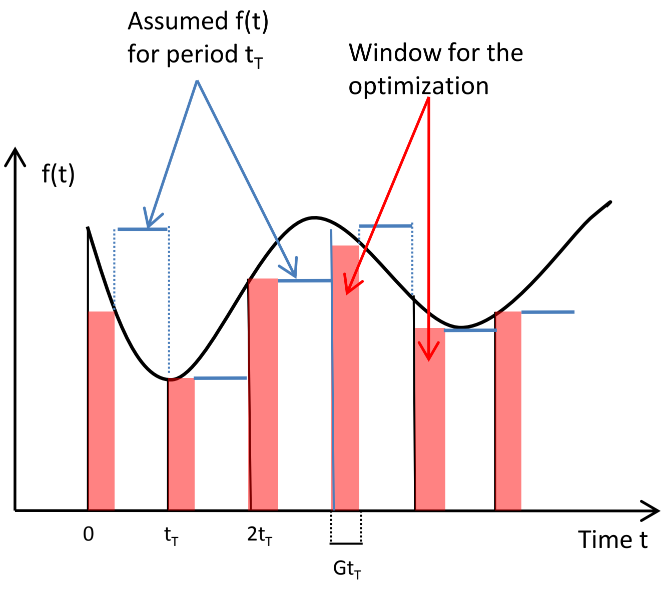


Figure 5.4: Dynamic Online Optimization [34]

5.5 Analysis of the Multi-Objective Optimization Problem in the TAG System

The concrete MOOP arising in the TAG system is described here with a very simple example. More complex setups and scalability studies are carried out in Chapter 7. For the simple example, two services are considered, for instance *iELSSI* and *TAG Database*, in the following referred to as $S1$ and $S2$ respectively, for simplicity. Each service has three associated deployments, and links are defined between all deployments of $S1$ and all deployments of $S2$. Each deployment has a performance index and a usage index, and each link also has a performance index. The attribute values are provided in Tables 5.2 and 5.3. The goal is to select deployments for the abstract workflow composed of $S1$ and $S2$, in this order, conforming to the objectives stated in Section 5.3.2. The result is a concrete workflow composed of two deployments and, implicitly, a link between them. Figure 5.5 illustrates the abstract workflow and the possible combinations of deployments forming concrete workflows.

There are $3 \times 3 = 9$ possible concrete workflows.

Figure 5.6 shows the non-dominated solutions, knowing that the performance index is maximized, while the combined usage index is minimized. There are no constraints in this example. The points $(5, 9.55)$, $(7, 12.35)$ and $(9, 21.14)$ correspond to the concrete workflows $S1D2-S2D1$, $S1D2-S2D2$ and $S1D3 - S2D1$ respectively. The first one is optimal regarding the usage index, the third one is optimal regarding the performance index. Which one is actually chosen depends on user preferences and, in the concrete case, on the optimization profiles. For example, if the objective weights are defined as follows: $w_{perf} \succ w_{usage}$ and the randomly assigned weights are $w_{perf} = 0.8$ and $w_{usage} = 0.2$, then:

- The overall utility value of $S1D2 - S2D1$ is: $9.55 \times 0.8 - 5.92 \times 0.2 = 6.456$
- The overall utility value of $S1D2 - S2D2$ is: $12.45 \times 0.8 - 8.30 \times 0.2 = 8.3$
- The overall utility values of $S1D3 - S2D1$ is: $2.02 \times 0.8 - 9.53 \times 0.2 = 15.71$

Thus, in this case $S1D3 - S2D1$ will be chosen. If however the objective weights are defined as follows: $w_{perf} \prec w_{usage}$ and the randomly assigned weights are $w_{perf} = 0.1$ and $w_{usage} = 0.9$, then:

- The overall utility value of $S1D2 - S2D1$ is: $9.55 \times 0.1 - 5.92 \times 0.9 = -4.373$
- The overall utility value of $S1D2 - S2D2$ is: $12.45 \times 0.1 - 8.30 \times 0.9 = -8.715$
- The overall utility values of $S1D3 - S2D1$ is: $22.02 \times 0.1 - 9.53 \times 0.9 = -6.375$

Thus, in this case $S1D2 - S2D1$ will be chosen. In order to illustrate a dynamic aspect reflected in the system itself, two attribute values have been changed. The changed values are:

- $perf(S1D1) = 8.92$
- $usage(S2D1) = 7.3$

The resulting Pareto points are displayed in Figure 5.7. The four points on the Pareto front are: $S1D1$-$S2D2$ $(11.24, 21.53)$, $S1D1 - S2D3$ $(9.64, 15.42)$ $S1D2$-$S2D2$ $(8.30, 12.45)$ and $S1D3$-$S2D1$ $(12, 21.14)$. In this case, the previously computed non-dominated points cannot simply be reused. However, two complete solutions reappear in this slightly changed example, namely $S1D3$-$S2D1$ $(9.53, 22.04)$ and $S1D2 - S2D2$ $(7, 12.35)$, and one part of a solution is present in both examples, namely $S1D2$. Thus, in such a case it can be useful to reuse existing knowledge about good solutions, in order to speed up the optimization process. Evidently, for such a simple example any checks for changes are most probably computationally more expensive than a new optimization run, but in huge systems, with many different deployments, this knowledge can be efficiently leveraged. Mechanisms to do so are discussed in Chapter 6.

5.6 Summary

The components and attributes of distributed, service-oriented systems are usually dynamic, because the underlying resources and the network are not stable, and system attributes also change with the way and intensity the system is used. Therefore, a QoS-aware service selection problem defined

Service	Deployment	Performance Index	Usage Index
S1	S1D1	1.99	4.55
	S1D2	2.37	1.61
	S1D3	9.25	5.22
S2	S2D1	4.63	4.31
	S2D2	6.73	6.69
	S2D3	1.09	8.09

Table 5.2: Services and Deployments in a Simple Example

Link	Performance Index
S1D1-S2D1	2.42
S1D1-S2D2	5.58
S1D1-S2D3	5.41
S1D2-S2D1	2.55
S1D2-S2D2	3.35
S1D2-S2D3	8.49
S1D3-S2D1	8.14
S1D3-S2D2	3.98
S1D3-S2D3	4.09

Table 5.3: Links in a Simple Example

on top of such a system is a dynamic optimization problem, i.e., the considered problem space as well as the optimization parameters change with time. Different categories of such dynamics are analyzed, taking the experience of the TAG system as example. This analysis reveals that some dynamics are related to the system itself (*system-inherent dynamics*), usually not predictable, and thus have to be actively detected. The second class covers *optimization dynamics*, which are generally predictable, potentially cyclic, and have a considerable impact on the solutions. The analysis of related work suggests that these categories should be treated separately in an optimization approach. The concrete optimization in the TAG system is carried out from two different perspectives, leading to two conflicting objectives. The resulting challenge is thus a dynamic multi-objective optimization problem. Such problems do not have a single solution, but a set of non-dominated solutions that form the so-called Pareto front. Classical techniques for approaching such problems have been briefly discussed. A simple concrete example verified that different changes have different impacts on the optimization problem and its solutions. The next chapter introduces a multi-objective optimization approach that allows acting and reacting efficiently to system changes.

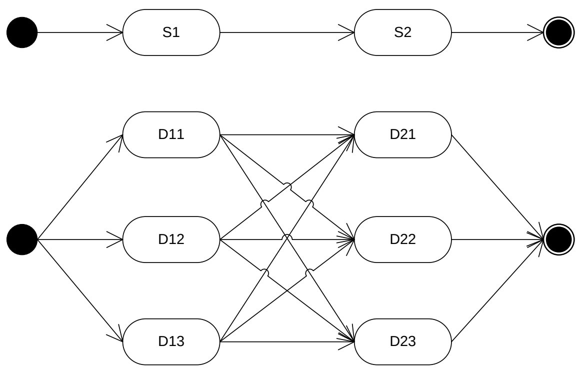


Figure 5.5: Abstract and Concrete Workflows in a Simple Example

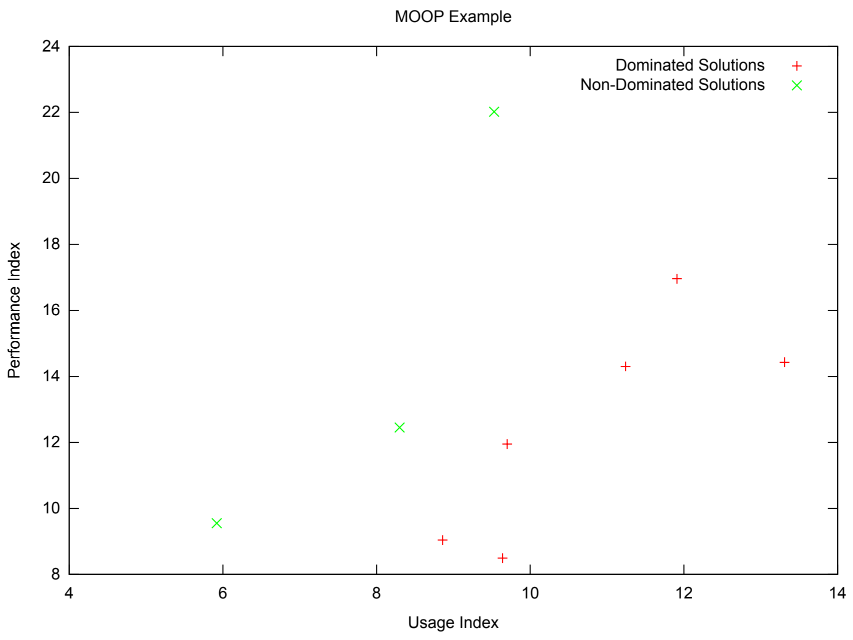


Figure 5.6: Pareto Optimal Points for the Simple Example

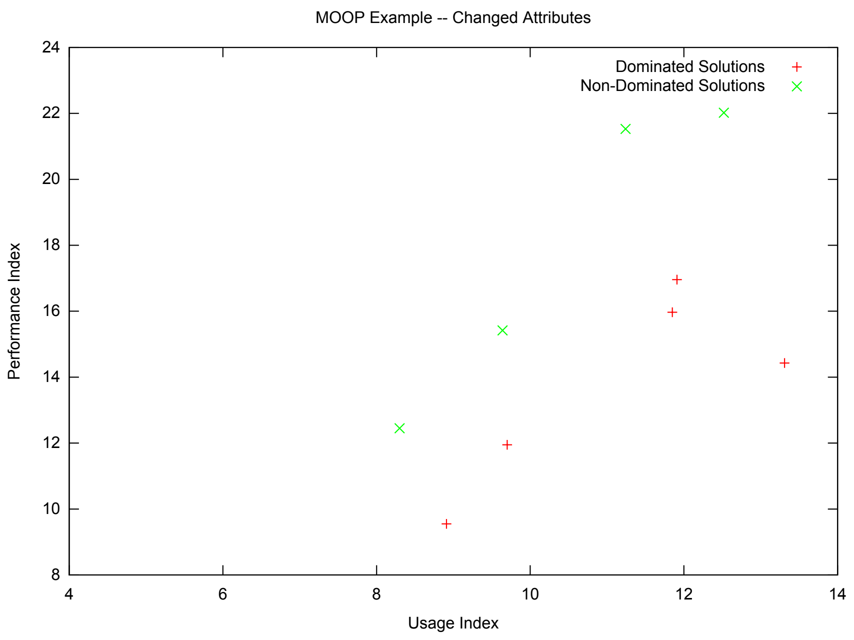


Figure 5.7: Pareto Optimal Points for the Simple Example with Changed Attributes

Chapter 6

Designing Genetic Algorithms for Service Selection Optimization Problems

After having defined the system environment and the concrete optimization problem, an algorithmic approach to solve the QoS-aware service selection problem is investigated. In order to be efficient and tailored to the dynamic characteristics of a heterogeneous, distributed system, this approach has to be able to detect changes in the environment and adapt to them. Genetic Algorithms (GA) have been widely proposed and surveyed to address dynamic multi-objective optimization problems in general, and have proved to be efficient in this area. Several authors applied GAs to QoS-aware service selection problems in particular. However, the approaches are mainly targeted at testing the application of existing multi-objective GAs to a simulated service selection environment, without taking into account system dynamics. The algorithms might thus work well in environments assumed as static, but there is no evidence on their ability to react and adapt to changes. Therefore, this chapter proposes an adaptive and dynamic GA, named AD-MOGA, which is designed based on the systematic analysis of the specific dynamic aspects presented in the previous chapter. An introduction to multi-objective GAs and techniques for adapting them to dynamic environments is provided in order to demonstrate the reasoning behind the approach. A comparison with related work is carried out to show the originality of the contribution.

This chapter is organized into sections as follows. Section 6.1 defines the basic concepts of GAs required to understand the reasoning behind this chapter, and their application to multi-objective optimization problems. In Section 6.2, techniques for adapting genetic algorithms to dynamic environments are outlined and discussed. The motivation for applying GAs specifically to QoS-aware service selection problems is discussed in Section 6.3. Section 6.4 introduces and explains an adaptive and dynamic multi-objective genetic algorithm (AD-MOGA) designed for addressing dynamic QoS-aware service selection problems. Section 6.5 presents other works addressing the QoS-aware service selection problem by the means of GAs. Finally, Section 6.6 summarizes the contributions of this chapter.

6.1 Background on Genetic Algorithms

6.1.1 Basic Concepts

Genetic algorithms, first introduced by Holland [47], are heuristic search algorithms mimicking natural evolutionary processes. They belong to the broader class of Evolutionary Algorithms (EA). A GA uses concepts from natural evolution, such as *reproduction* and *mutation*, to converge a set of candidate solutions (referred to as *individuals*) in a search space towards an optimum. When a GA is applied to a specific problem, this problem first has to be encoded, then so-called genetic operators can be applied to the encoded representation. In order to understand the functioning of a GA in general and the one proposed in this chapter in particular, it is important to define the concepts and building blocks of a GA. The following terms are all referring to concepts from natural evolution and can be interpreted in analogy to evolution.

Gene. Refers to a part of a chromosome, i.e., a partial solution encoding.

Chromosome. Collection of genes encoding a candidate solution to a given problem.

Individual. Actual potential solution to a problem, represented as a chromosome.

Population. Set of n individuals at a given point in time, where the input parameter n defines the population size.

Generation. Iteration of a GA. The maximal number of generations is an input to the algorithm and can be used as a termination condition.

Fitness. Refers to the quality of a solution or chromosome, computed based on the *fitness function* that has to be defined for each problem.

Genotype. Representation of a solution or chromosome. Binary and real-value representations are common.

Phenotype. The actual manifestation of the individual, resulting from the expression of the genotype.

The steps of an evolutionary algorithm are listed in Algorithm 3 and are described in the following.

Initialization. Refers to the creation of the initial population $P(0)$. It can either be created randomly, or by using existing knowledge. The size of the population, i.e., the number of individuals per generation, is an input parameter that has to be defined.

Evaluation. During evaluation, a fitness value is assigned to each individual in a generation. This step is independent of the algorithm and is externally defined, as it fully depends on the specific problem to be solved. The evaluation is applied on the phenotype.

Crossover. The crossover operator takes n individuals as input (called the *parents* – commonly $n = 2$) and generates one or two new individuals, called *children* or *offspring*. The idea behind the crossover operator is to mimic the sexual reproduction process by combining genes from two parents to form new individuals. The goal is to combine good partial solutions to eventually form even better solutions. The crossover operation and its frequency have to be carefully chosen and tailored to the given problem. There exist different crossover techniques, such as one-point crossover (a random crossover point is chosen and all genes right of that point are exchanged between the parents), two-points crossover (two cross-over points are randomly chosen and the middle parts are exchanged) and uniform crossover (each gene is exchanged or not with equal probability).

Mutation. As opposed to crossover, mutation is an asexual genetic operator. It is an operation on a single individual, generally a bit flip (on binary chromosomes) occurring at a certain, defined probability. The purpose of the mutation operator is to ensure that new genetic material enters the population, thus avoiding the solution to early converge towards a local optimum.

Selection. Selection of individuals occurs at two stages in a GA: when individuals are selected as parents to produce offspring (cf. mating pool in Algorithm 3), and when individuals are selected to form the next generation. The latter is also referred to as *reproduction*. There exist several basic types of reproduction. In *generational reproduction*, all individuals are replaced in the transition from generation t to generation $t+1$. In *steady-state reproduction*, only one or two individuals (usually the worst, i.e., the ones having the lowest fitness values) are replaced from one generation to the next. The intermediate solution is referred to as *generational reproduction with elitism* and allows a certain number of top individuals (with the highest fitness, i.e., the "elite") to survive to the next generation. The overall goal of selection is to target the search to the most promising areas of the search space.

To summarize, the overall goal of a GA is to generate a population of individuals representing optimized solutions to a given problem, by evolving a random initial population by mixing genetic information (crossover), introducing new genes (mutation) and selecting individuals with higher fitness (selection) to survive across generations. This cycle is represented in Figure 6.1 and the process is detailed in Figure 6.2 with a simple example. Six bit-encoded chromosomes form a population, the fitness function is defined as the sum of the occurrences of 1. The figure depicts one iteration of the algorithm, where the two individuals with the highest fitness values are selected for mating. A one-point crossover at a position defined randomly is then applied to them, resulting in two children. This is followed by a mutation (bit-flip), again at a random position. The purpose of this example is only to illustrate the concepts defined above. Real-world examples are of course more complex and a single iteration does not necessarily lead to an improved solution.

Since their introduction, GAs have been successfully applied to numerous optimization scenarios. They are used for addressing single- and multi-objective combinatorial optimization, fuzzy optimization, scheduling, network design and many more [42]. For numerous examples of concrete problem descriptions and the application of GAs to them, the reader is referred to [97].

The implementation of the genetic operators for QoS-aware service selection problems is motivated in Section 6.3 and described in Section 6.4.

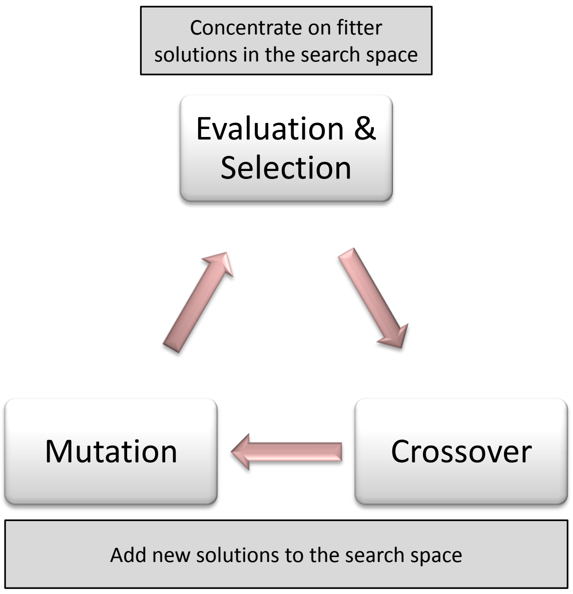

Concentrate on fitter solutions in the search space
Evaluation & Selection
Mutation
Crossover
Add new solutions to the search space

Figure 6.1: Genetic Algorithm: Cycle of Operations

6.1.2 Genetic Algorithms for Multi-Objective Optimization

GAs are particularly well suited for multi-objective optimization problems (MOOP) and this research area has received much attention in the last two decades [42]. The concepts of evolving populations and diversity used in GAs allow searching the entire search space and, in the multi-objective case, the entire Pareto front. They are thus structurally suited to address MOOP and in fact they are the most popular metaheuristic for solving MOOP [57]. A GA designed for single-objective optimization problems can be adapted to the multi-objective case by using special fitness functions and employing techniques to raise the diversity in a population. The pseudocode of a basic GA applied to MOOP and introducing the Pareto concept is shown in Algorithm 4. Many different Multi-Objective Genetic Algorithms (in the following referred to as MOGA) implementing sophisticated concepts for specific use cases, have been proposed. Konak, Coit and Smith [57] provide a comprehensive general tutorial for the design of MOGA. According to the authors, the following four areas have to be addressed in terms of design choices:

1. Fitness functions
2. Diversity
3. Elitism
4. Constraint handling

The proposed MOGA mainly differ in the implementation of those aspects. The following short discussion of those four aspects is based on [57].

The classical approach for designing a multi-objective fitness function is the weighted-sum approach discussed in Chapter 5 (Section 5.4.3). In this approach, weights are assigned to the objectives

Algorithm 3: Genetic Algorithm

```
1  t = 0;
2  initialize population $P(0)$;
3  evaluate $P(0)$;
4  repeat
5      selection: $P(t)$;
6      copy selected individuals into mating pool: $M(t) = s(P(t))$;
7      crossover: $M'(t) = c(M(t))$;
8      mutations: $M''(t) = m(M'(t))$;
9      update population:$P(t+1) = u(P(t) \cup M''(t))$;
10     evaluate $P(t+1)$;
11     $t = t + 1$;
12 until termination condition true;
```

Algorithm 4: Genetic Algorithm with Pareto Pool

```
1  $t = 0$;
2  initialize population $P(0)$;
3  repeat
4      selection: $P(t)$;
5      copy selected individuals into mating pool: $M(t) = s(P(t))$;
6      crossover: $M'(t) = c(M(t))$;
7      mutations: $M''(t) = m(M'(t))$;
8      evaluate all objectives;
9      update Pareto $E(t)$;
10     update population: $P(t+1) = u(P(t) \cup M''(t))$;
11     evaluate $P(t+1)$;
12     $t = t + 1$;
13 until termination condition true;
```

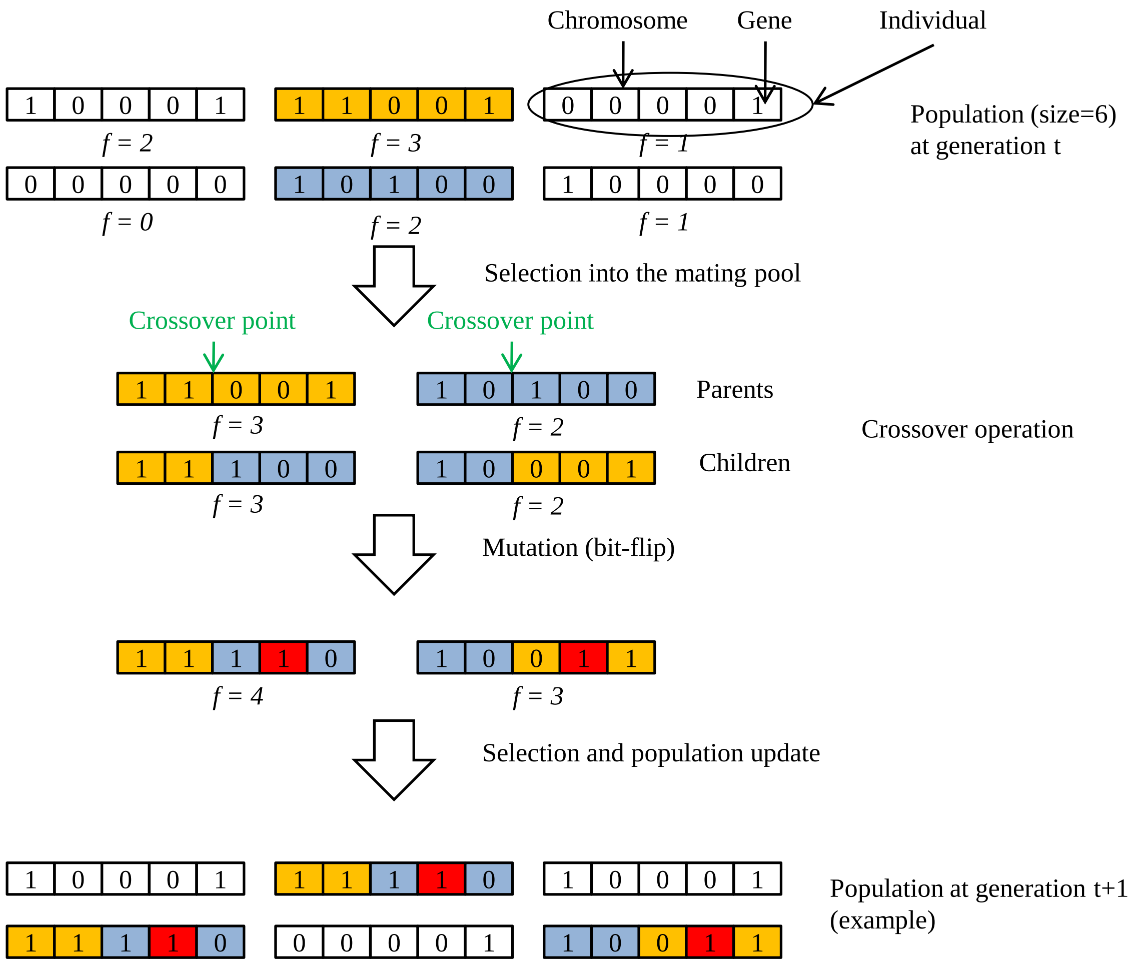


Figure 6.2: Steps of a Genetic Algorithm (f denotes the Fitness)

that are then combined into a single objective function. Because the assignment of weights is non-trivial, attempts have been made to assign weights automatically. For example, different random weights can be assigned for each run of the algorithm, to assure that the entire search space is explored. While this method is a priori (in the terminology introduced in Chapter 5, Section 5.4.3), most multi-objective GAs are a posteriori [17]. An alternative design decision is to alter the objective functions, as implemented in the vector evaluated GA (VEGA). In this implementation, the population is divided into K subpopulations of equal size, where K is the number of objectives in the considered optimization problem. Each of these subpopulations is evaluated regarding one objective, then the subpopulations are combined and crossover and mutation operators are applied. This method is relatively easy to implement, but it has been observed that while it produces good solutions regarding one objective, these solutions are poor with respect to the other objectives. Finally, a third alternative approach is called Pareto-ranking. The underlying idea is to assign fitness values based on ranks instead of objectives. The rank of a solution can be determined based on the number of solutions it dominates, giving a better rank to solutions in sparse areas of the search space, to promote diversity.

The second design issue concerns diversity. Promoting diversity in a population is important to obtain solutions from all regions of the Pareto front, and avoiding the convergence to a local optimum. If diversity is not actively promoted, a phenomenon called *genetic drift* is likely to occur: the individuals populate a few clusters, while other regions of the search space remain unpopulated. Three approaches to address diversity in MOGA are outlined. First, *fitness sharing* can be applied. In this approach, the computed fitness values are altered in such a way that solutions in dense areas are penalized, whereas solutions in sparse, unexplored areas are given better fitness values. Thus, the latter solutions have a higher probability to survive. It is however challenging and potentially computationally expensive to determine sparse and dense areas. Additionally, a sharing parameter has to be defined. The second approach, *crowding distance*, tries to overcome these issues by sorting the solutions and assigning crowding distances to each solution per objective. Third, in the *cell-based density* approach, the criterion space is divided into K-dimensional cells and the solution density is defined as the number of solutions in the same cell.

Elitism is about keeping the best solutions, and ensuring that they survive to the next generation. In the context of MOOP, all non-dominated solutions can be considered as elitist solutions, but it can be impossible to keep them all, because the number of non-dominated solutions can be very large. There are two basic approaches for implementing elitism in MOGA: keeping a certain number of non-dominated solutions inside the population throughout the iterations, or keeping them in a separate list and reintroducing them into the population at a later point.

Finally, it has to be decided how to handle constraints in MOGA. There are four basic approaches. First, infeasible solutions can simply be discarded. This is referred to as *death penalty*. Second, infeasible solutions can be given a penalty reducing their fitness. Third, the genetic operators can be designed in such a way that they produce only feasible solutions. Fourth, infeasible solutions can be transformed into feasible ones, which is referred to as *repair*. All these methods that were originally introduced for single-objective GAs can be adapted to the multi-objective case. However, introducing a penalty function is not directly applicable if the fitness assignment is based on non-dominance ranks instead of the objective function values.

The above-mentioned design considerations are summarized in Table 6.1. They serve as guideline for the design of the MOGA proposed in this thesis.

6.2 Dynamic Genetic Algorithms

Dynamic optimization problems have been outlined in Chapter 5, Section 5.4.4. Since adaptation to changes is crucial in Nature to ensure the survival of species, and GAs mimic those processes, they are natural candidates to efficiently deal with dynamic environments, i.e., to efficiently react to changes and adapt to them. When no adaptation techniques are used, the only way to react to a change is to restart the optimization with the changed parameters and conditions. However, on one hand, this can be a long process in large problem settings, and on the other hand the environment can even change during the optimization, i.e., the optimization outputs a solution or a set of solutions that are not optimal or nearly optimal anymore, given the changed conditions. According to [16], the approach of simply restarting the optimization problem after a system change has occurred has

Design Item	**Approaches**
Fitness Functions	Weighted Sum Approaches
	Altering Objective Functions
	Pareto-based Approaches
Diversity	Fitness Sharing
	Crowding Distance
	Cell-based Density
Elitism	Inside the population
	In an extra list
Constraint Handling	Death Penalty
	Penalty Function
	Crafting Genetic Operators
	Repair Strategies

Table 6.1: MOGA Design Considerations

the following shortcomings:

- Solving a problem from scratch can be too time consuming in large problems.
- A change can be difficult to discover, or remain undetected for some time.
- If changes are small, it may not be necessary, possible or economically justifiable to adapt the solutions.

In [16], the author concludes that three main challenges have to be addressed by approaches dealing with dynamic systems:

- The algorithm should be designed in such a way that it can easily and efficiently adapt the solution to changes in the environment.
- However, it should first investigate the costs of changes and determine a trade-off between solution quality and costs of changes.
- Changes can be very small and frequent and have almost no impact. In such a case, it is better to have robust solutions maintained through those small changes.

This section surveys techniques extending GAs to be able to handle dynamic environments. It is mostly based on the state of the art provided by Branke [16] and on the thesis of Weicker [96]. Additional references are included where relevant.

6.2.1 Algorithm Restart or Re-Initialization

The most straightforward approach when confronted with a changed environment is to simply restart the optimization process from scratch. However, depending on the nature and severity of the change, it can be easy and beneficial to reuse information from previous optimization runs, i.e., good individuals. The reuse of good individuals from previous optimizations has to be done carefully though, since there is a tradeoff between exploration and exploitation. Using too many old individuals can lead to an early convergence of the algorithm in a local optimum. Several studies revealed that only a small portion of the old population should be transferred to the initial one of a new optimization run [16].

6.2.2 Diversity after Changes: Adapting the Mutation Rate

When a change occurs, it is important to ensure diversity in order to enable the algorithm to spread its search. Since mutation is the central operation for ensuring diversity in the population, its rate can be adapted upon changes. A method called *hypermutation* suggests to increase the mutation rate after a change has been detected. In another method, named *random immigrants*, randomly generated individuals are introduced in every generation. Experiments have shown that hypermutation is well suited in slowly changing environments, while random immigrants are most beneficial when important changes happen at a frequent rate [16]. It has also been suggested to change the mutation rate through self-adaptation [16].

6.2.3 Diversity along the Runtime: Modifying the Selection

Instead of changing the mutation rate to react to changes, some authors suggested to change the selection process [16]. Examples are the diversity-preserving techniques described in Section 6.1.2, namely *fitness sharing*, *crowding distance* and *cell-based density*. The underlying idea is to emphasize the search on sparsely populated regions of the search space. In other approaches, the diversity in the population can be an explicit parameter that has to be determined and provided.

6.2.4 Memory-based Techniques

If environments change periodically, i.e., similar environmental conditions keep reappearing, it is intuitive to memorize good solutions and reuse them when the same conditions reappear. This memory can be *implicit* or *explicit*.

Implicit memory leverages redundant representation, and allows keeping parts of previous solutions in the evolutionary process. Prominent methods include the usage of diploid or polyploid representations [96]. In biology, diploid cells have two copies of each chromosome, and only the dominant one gets expressed in the phenotype. In analogy, the recessive alleles can be used to maintain parts of previous solutions in the population. If an environmental change occurs, the alleles can for example be inverted, i.e., the dominant one becomes recessive and vice versa. Specific algorithms based on implicit memory and tailored to specific problems outperform algorithms without memory in simulation. However, it is difficult to determine whether and how this implicit memory is used.

GAs with explicit memory make use of stored individuals that can be reintroduced in the population. For example, each individual can keep its ancestors in memory. When an environmental change occurs, those ancestors are also evaluated and replace the current individuals, given they outperform them. Another approach is to selectively store the best individual of each generation in a separate memory, and consider this set of individuals as potential parents for crossover. Branke [16] points out that it is crucial to combine memory-based techniques with mechanisms to promote diversity, in order to avoid early convergence in a local optimum. The author also highlights important design considerations when using the explicit memory approach:

- When and which individuals should be stored in the memory?
- How many individuals should be stored in the memory and which ones should be replaced?
- Which individuals should be retrieved from the memory to be reinserted into the population, and when?

Explicit memory techniques proved to be efficient in alternating problems, with limited different problem states but a potentially high change frequency [96].

6.2.5 Multi-Population Techniques

The population of a GA can be divided into a number of subpopulations and a specific task can be assigned to each subpopulation. For instance, Branke [16] suggests an approach called *Self-Organizing Scouts* where the population is split as soon as a peak is found: one subpopulation then has to monitor and follow this peak, while a larger subpopulation is used to continue the search for other peaks in other areas of the search space.

6.2.6 Comparison

Other approaches as well as combinations of the above-mentioned techniques have been presented. A detailed survey can be found in [16] and [96]. Weicker [96] also proposed a problem-techniques mapping based on his detailed analysis of dynamic environments and related GAs addressing those dynamics. However, this author points out that this mapping can only be considered as a first impression, and that it is reflecting areas in which researchers made specific contributions. It does thus not mean that specific methods cannot be successfully applied to scenarios not mentioned in the mapping. Therefore, research in this area is mainly driven by the application of a technique or combination of techniques to a specific problem setting with specific characteristics in the underlying dynamics. In Section 6.4.4 such a hybrid approach is presented for QoS-aware service selection problems.

6.3 Motivation for Using GAs in QoS-Aware Service Selection

As described in the previous two sections, GAs are well-suited for solving multi-objective optimization problems, and there are several methods to make them especially efficient in dynamic environments. The strong arguments to apply GAs to QoS-aware service selection problems are the following:

1. **Multiple objectives.** Most QoS-aware service selection problems have multiple competing objectives. As pointed out by Li et al. in [60], in practice it is often very difficult to combine multiple objectives into a single one based on utility weights, as those weights are not known

a priori. Also, it is often preferable to produce a set of Pareto-optimal solutions representing a trade-off, and let a user (or automated mechanism) choose one. Evolutionary algorithms are a popular metaheuristic to produce Pareto-optimal solutions for optimization problems with competing objectives.

2. **Dynamics.** As developed in Chapter 5, distributed, service-oriented system with centralized control instance are dynamic in several aspects. These dynamics can be described and classified. Various techniques exist to adapt GAs to dynamic environments. Thus, based on a careful analysis of system-specific dynamics, customized GAs can be designed and implemented.

3. **Parameter tuning.** GAs require multiple input parameters. On one hand, it might not always be easy to determine them. On the other hand, if effort is put on determining them properly, they can be used to efficiently customize GAs and tailor them to specific environments, here in particular to characteristics of distributed, service-oriented systems.

4. **Computational complexity.** If the service selection problem is formulated as an integer programming problem, the number of required variables increases with the number of deployments available. Assuming a problem space with n services and m_i deployments per service i, and an associated model with $\sum_{i=1}^{n} m_i$ integer variables y_{ij} such that $\sum_{j=1}^{m_i} y_{ij} = 1$ and $y_{ij} \in \{0, 1\}$. $y_{ij} = 1$ if service S_i is bound to deployment D_{ij}, and 0 if not. Thus, if the number of deployments m_i increases, the problem complexity increases [22]. In a GA however, assuming an integer encoding, the size of the genome depends only on the number of (abstract) services n. The number of deployments only influences the size of the search space.

5. **No linearity constraints.** GAs do not impose linearity constraints on the fitness and constraint functions.

However, it has to be pointed out that for small problem setups, GAs may be of poorer computational performance compared to integer programming for instance [22]. Thus, the problem size, i.e., the number of services and deployments as well as the structure and length of the workflows have to be taken into account when designing a solution approach.

Although the TAG system is not very big as of today, it is expected to grow. Therefore, a scalable approach has to be adopted. Additionally, the scalability has to be ensured to suggest the applicability of the approach to other real-world systems, using the TAGs as a testbed. Taking all the previously mentioned into account, a novel GA-based deployment selection optimization framework is proposed in the next section. The main contributions are:

- A systematic approach to design GAs in order to address dynamics encountered in QoS-aware service selection problems.

- The validation of the approach.

6.4 An Adaptive and Dynamic Multi-Objective Genetic Algorithm for QoS-aware Service Selection Problems

6.4.1 Problem Encoding

When designing and implementing a GA, it is important to choose a proper encoding, suited for the considered problem. In [16] the author points out that the genetic encoding as well as the operators define the search landscape the GA operates on. According to the author, this landscape should be small, contain the optimal solution, and as few infeasible solutions as possible. Typical encodings are *binary* and *integer* encodings. In QoS-aware service selection problems, integer encoding is most common. For example, in [60] a vector of concrete services (deployments) is specified as $\overline{x} = [2, 5, 7, 6]^T$, where 2 refers to the second deployment from the first service, 5 to the fifth deployment from the second service, 7 to the seventh from the third service, and so on. According to [80], integer encoding has several advantages over binary string encoding. First, it is a natural way of representation for many problems, second it eases the implementation of genetic operators, and thus improves the overall algorithm computational efficiency. Although the example provided above is strictly speaking an integer encoding, each integer is in fact a *key* or *pointer* to a deployment. Additionally, this structure assumes a sequential workflow, and it is unclear how to represent the general flow structure. The encoding can thus be generalized as follows:

- Each gene in a chromosome is a *pointer* to a deployment. If an abstract workflow is provided as input, the list of deployments per service can be generated according to the system ontology. The pointer corresponds to the `id` as defined in 4.2.2.
- Helper genes are introduced to allow the expression of general flow structures. An example is provided in Figure 6.3, where two helper genes, $\texttt{AND}_s$ (AND-split) and $\texttt{AND}_m$ (AND-merge), are used to indicate a parallel workflow structure. These helper genes are excluded from crossover and mutation, but they are used for computing the fitness of a chromosome.

The specific encoding is chosen in order to reflect the structure of the problem. It requires however also specific genetic operators, as will be pointed out in the following subsections. The search space is defined by the abstract input workflow W_0 and the *system*, i.e., the available deployments per service. The data regarding the components and their attributes can be queried from the central QoS registry that implements the ontologies introduced in Chapter 4. In the TAG case, this corresponds to the TASK service catalog.

6.4.2 Fitness Functions

The optimization objectives for the concrete problem studied in this thesis have been presented in Chapter 5 (Section 5.3.2). The fitness functions are derived from these objectives and from the optimization profiles presented in Section 5.2.2. As discussed in Section 5.4.1, there exist several approaches to deal with multiple objectives and most of them can be applied to genetic search and can even be extended in the specific context of multi-objective genetic algorithms.

There are two objectives, so strictly speaking there are two fitness values for each chromosome encoding a concrete workflow. One fitness value reflects the overall workflow performance index

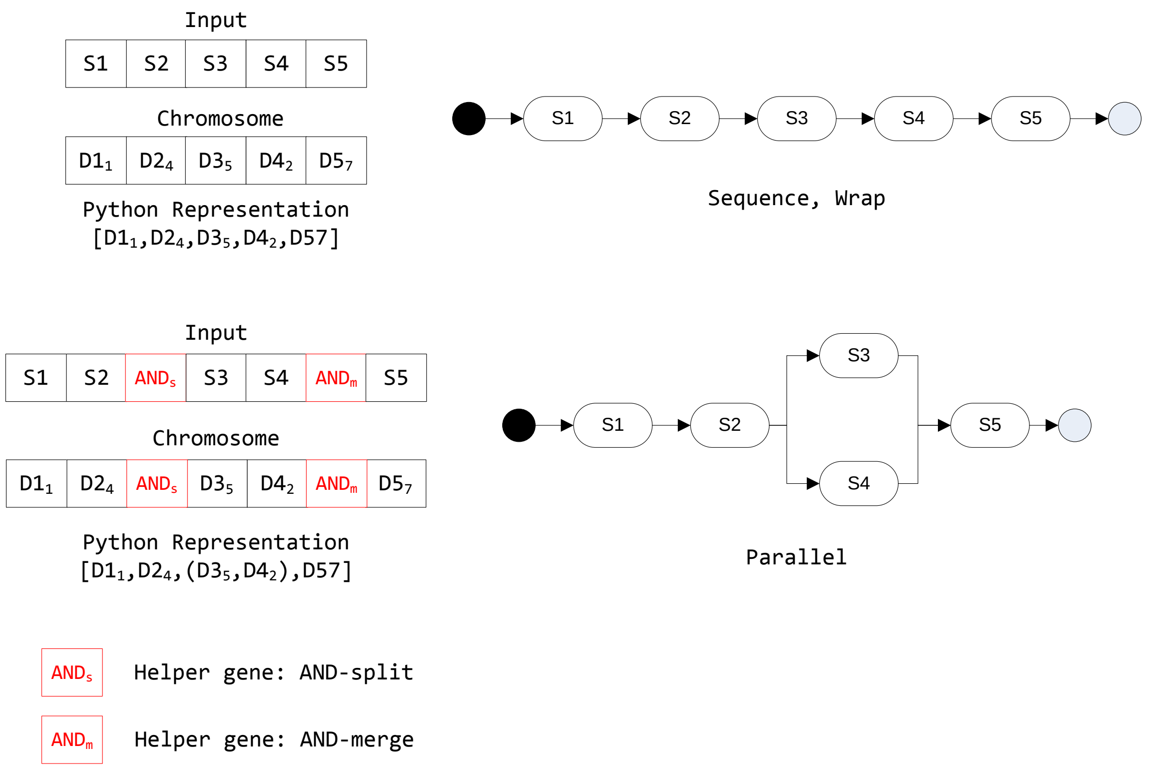


Figure 6.3: Chromosome Encoding

$p(W_0, W)$, the second one the cumulative usage index $u(W_0, W)$ over all services in the workflow. This can be easily extended to the general case with q objectives. As stated in Section 5.2.2, there are four different cases regarding the objective weights. They define ranges for the weights rather than concrete values, which are difficult to obtain. This preference information expressed in the optimization profile can be used to guide the genetic search. It has to be noted that, as pointed out in [42], weighted-sum approaches in GAs are different and more powerful than in non-evolutionary techniques. In fact, in GAs weights can evolve and being adapted within the evolutionary process, which ensures a greater diversity than fixed weights. Additionally, it is not required to define an exact weight vector. AD-MOGA adopts a slightly extended version of the random weight approach introduced by Ishibuchi and Murata in [50]. The underlying idea is to assign random weights for the objectives at each step (generation) of the GA. The random weights w_k are determined as follows:

$$w_k = \frac{r_k}{\sum_{n=1}^{q} r_n}, \quad k = 1, 2, ...q \tag{6.1}$$

where $r_k, k = 1, 2, ..., q$ are random numbers such that $r_k \in [0, 1]$ and $\sum_{k=1}^{q} r_k = 1$. For AD-MOGA, the definition of random weights is extended as follows:

$$[w_k]_{OP(t)} = \begin{cases} \frac{r_k}{\sum_{n=1}^{q} r_n} \text{ and } r_i > r_j & \text{if } w_i \succ w_j \\ \frac{1}{q} & \text{if, for } \textit{all} \text{ pairs } (i,j),\ w_i \sim w_j \\ \frac{r_k}{\sum_{n=1}^{q} r_n} \text{ and } r_i < r_j & \text{if } w_i \prec w_j \\ \frac{r_k}{\sum_{n=1}^{q} r_n} & \text{if } w_i \ ?\ w_j \end{cases} \tag{6.2}$$

where $r_k, k = 1, ..., q$ are nonnegative random numbers such that $r_k \in [0,1]$, $\sum_{k=1}^{q} r_k = 1$, and r_i and r_j are the random numbers for determining the weights of objective functions i and j respectively, with $i, j = 1, ..., q$ and $i \neq j$. The resulting **weighted fitness function** of the workflow (service combination) W at generation i is as follows:

$$\textit{fitness}(W)_i = [w_1]_{OP(t)} \cdot p(W_0, W) - [w_2]_{OP(t)} \cdot u(W_0, W) \tag{6.3}$$

where $p(W_0, W)$ and $u(W_0, W)$ are as defined in Section 5.3.2 and $OP(t)$ is the optimization profile active at time t, as defined in Section 5.2.2. Before each selection, i.e., in each generation, the weights are recomputed according to Equation 6.2.

6.4.3 Genetic Operators and Multi-Objective Design Considerations

This section details the specification of the genetic operators in AD-MOGA, as well as the multi-objective design considerations. The genetic operators in AD-MOGA are defined as follows:

Selection. The selection mechanism implemented in AD-MOGA is a classical roulette-wheel selection, in which the selection probability of an individual is proportional to its fitness. Therefore, the fitter an individual, the higher are its chances to be selected as a parent and produce offsprings via the crossover operator. The roulette-wheel selection depends on the fitness function and thus, for a population $P = \{A_1, ..., A_r\}$ where $A_i \in G$ and G is a genotypic search space, it can be defined as in [96]: $S^f : G^r \to G^s$ where s individuals out of r individuals are selected, $r, s \in \mathbb{N}$, $s \leq r$, and $S^f(P) = \{B_1, ..., B_s\}, B_j \in P$. That is, a fraction of the individuals (usually two) is selected out of all the individuals for reproduction. One method is to copy individuals according to their fitness to a temporary pool. For example, an individual with a fitness value of 5 is copied 5 times, an individual with a fitness value of 20 is copied 20 times, etc. Then, when randomly selecting an individual out of this pool, the chance to select one with fitness value 20 is 4 times higher than to select one with fitness value 5. The sample individuals are independent, i.e., it is a sampling with replacement. It is possible to select two identical individuals. In this case, the crossover operator cannot introduce a change, but the mutation operator can.

Crossover. AD-MOGA implements a 1-point crossover, although the operator can easily be altered (for instance into a 2-point crossover, which is also commonly used) and the implications can be assessed. The crossover point can be random, i.e., at any position of the chromosome, also at a helper gene position. In [96] the cross-over or recombination operator is defined for $r \geq 2$ parents and $s \geq 1$ offspring as $C^{\xi} : G^r \to G^s$ where G is a genotypic search space $r, s \in \mathbb{N}$. This general definition can be directly applied to the presented use case. As pointed out by Weicker in [96], in GAs the emphasis is put on recombination as the main operation to evolve individuals through generations, which is also what happens in Nature. Therefore, recombination is usually applied with a rather high probability of about 0.6 to 0.7. Parameter values tested for AD-MOGA are discussed in Chapter 7.

Mutation. While mutation is often referred to as a "bit-flip" operation, it has to be re-defined for service/deployment selection problems and can be referred to as "deployment flip" operation. The general operator is defined as [96]: $M^{\xi} : G \rightarrow G$ where G is a genotypic search space and $\xi \in \Xi$ is a random number within the range of the chromosome length. Applied to the service selection problem, the operator can be defined as:

$$M^{\xi} : D_i(S^{\xi}) \rightarrow D_j(S^{\xi}), i \neq j \tag{6.4}$$

where S_{ξ} is the service at position ξ in the workflow. This means that a mutation of a deployment is defined within its service class, i.e., a deployment can only be replaced by another deployment belonging to the same service. As pointed out in [96], mutation acts a background operator in GAs (while cross-over is the deciding one) and typically has a probability around 0.01. Again, parameter values tested for AD-MOGA are discussed in Chapter 7.

As discussed in Section 6.1.2 and summarized in Table 6.1, specific choices have to be made to adapt GAs for multi-objective optimization problems and ensure diversity across generations. In AD-MOGA the following techniques are implemented:

Fitness. The individuals are evaluated based on the two objective functions, leading to two fitness values, and non-dominated solutions are identified and copied to the Pareto pool $E(t)$.

Diversity. The diversity of the population is ensured by the random weights assigned at each generation (in certain ranges, cf. 6.4.2). Techniques such as fitness sharing and density calculations tend to be computationally expensive, which makes them problematic in large problem setups in which the optimization has to be done online, on request. The diversity preserving capability of AD-MOGA is evaluated in Chapter 7.

Elitism. Elitism is implemented inside the population. A Pareto pool $E(t)$ is initially created and updated at each generation. It contains all non-dominated or Pareto solutions of the population at generation t. Note that the individuals that are kept in the Pareto pool are also part of the search population $P(t)$. When a new population is created at generation $t + 1$, N_{elite} individuals from the Pareto pool $E(t)$ are combined with $N_{pop} - N_{elite}$ individuals from $P(t)$, after crossover and mutation. While N_{pop} is a static parameter throughout generations, N_{elite} has to be updated at each generation, because the number of Pareto solutions cannot be known in advance. N_{elite} has to be chosen such that $0 < N_{elite} < N_{pop}$. Good (relative) ranges for N_{elite} are discussed in Chapter 7. The update of the Pareto pool at generation $t + 1$ is done as follows: all Pareto solutions of $P(t + 1)$ are determined and compared to the individuals in $E(t)$. $E(t + 1)$ is then populated with all non-dominated solutions from the set $E(t) \cup Pareto(t + 1)$ where $Pareto(t + 1)$ are the non-dominated solutions from $P(t + 1)$.

Constraint Handling. In the considered problem, constraints are not defined by default, but specific constraints on aggregated QoS attributes can be enabled via the optimization profile

OP(t). If constraints are defined, the related aggregated QoS value is calculated for every individual, and infeasible solutions are discarded, i.e., their fitness is set to 0.

Putting all these operators and techniques in context, the general outline of AD-MOGA is provided in Algorithm 5.

Algorithm 5: AD-MOGA: General Outline

```
1  $P(t)$: population at generation $t$;
2  $E(t)$: Pareto pool at generation $t$;
3  $Elite(t)$: pool of elite individuals at generation $t$;
4  $N_{pop}$: total number of individuals in the population at any generation;
5  $N_{pareto}(t)$: number of individuals in the Pareto Pool at generation $t$;
6  $N_{elite}(t)$: number of elite individuals to keep at generation $t$;
7  $C^{\xi}$: Crossover operator;
8  $M^{\xi}$: Mutation operator;
9  $t = 0$;
10 initialize population $P(0)$ of size $N_{pop}$;
11 evaluate $P(0)$ regarding $f_k, k = 1, ...q$ (for $q$ objective functions);
12 determine non-dominated solutions in $P(0)$;
13 copy non-dominated solutions to Pareto Pool $E(0)$ and determine $N_{pareto}(t)$;
14 repeat
15     set $N_{elite}(t)$ such that $0 < N_{elite}(t) < N_{pareto}(t)$;
16     copy $N_{elite}(t)$ individuals from $E(t)$ to $Elite(t)$;
17     calculate random weights according to Equation 6.2;
18     calculate weighted fitness for all individuals in $P(t)$ according to Equation 6.3;
19     select $N_{pop} - N_{elite}$ parents based on roulette wheel selection;
20     copy the selected $N_{pop} - N_{elite}$ parents to the mating pool $M(t)$;
21     perform crossover: $M'(t) = C^{\xi}(M(t))$ with probability $p_{crossover}$;
22     perform mutation: $M''(t) = M^{\xi}(M'(t))$ with probability $p_{mutation}$;
23     update population: $P(t+1) = M''(t) \cup N_{elite}(E(t))$ ;
24     $t = t + 1$;
25     evaluate $P(t)$ regarding $f_k, k = 1, ...q$ (for $q$ objective functions);
26     determine non-dominated solutions in $P(t)$;
27     update $E(t)$ and $N_{pareto}(t)$;
28 until termination condition true;
```

6.4.4 Adaptability to Changes

Based on the application-driven analysis of system changes presented in Chapter 5 and the state of the art regarding dynamic GAs, a change-action categorization is proposed in Table 6.2. The term *staging* in the table refers to the staging phase as defined in Section 6.4.5. *SP*(t) and *OP*(t) refer to system and optimization profiles, respectively. *PM* refers to *Persistent Memory* and is explained below, *TS* refers to the timestamp of an entry in the *PM* and *last_change_TS* is the timestamp of

1. Changes during an optimization run	
Change	**Adaptation**
(1): $SP(t)$ change in attribute values only	Back to staging, restart at the stopped generation, adapt the mutation rate and increase total generations.
(2): $SP(t)$ change in a component (addition or removal of a deployment)	Back to staging, restart at the stopped generation with a fraction of the last population and a randomly initialized part, adapt the mutation rate and increase total generations.
(3): Change in $OP(t)$	Adjust weights, adapt the mutation rate, and increase total generations.
2. Changes between two optimization runs	
Change	**Adaptation**
(4): (WF and $OP(t)$ in PM) AND ($TS \geq last\_change\_TS$)	Reuse previously computed solution.
(5): (WF and $OP(t)$ in PM) AND ($TS < last\_change\_TS$)	Initialization with random portion of previously computed last generation and adaptation of the mutation rate; both depending on the change impact.
(6): ((WF and $OP(t)$ in PM) AND radical change) OR (not yet stored WF or $OP(t)$)	Random initialization.

Table 6.2: Change-Action Mapping in AD-MOGA

the last change in the system.

Principally, two cases are distinguished: changes during an optimization run, and changes between two subsequent optimization runs. In the former case, a side-process can periodically query the registry for changes and, if present, analyze them. This supposes however that the optimization is taking a considerable amount of time, hence either a very large system is assumed, or the optimization process is continuously run. In this case, if changes are detected on QoS attribute values only, those changes are first staged into the algorithm process (requiring a registry connection and query), then analyzed regarding their impact (cf. Section 5.2.3), and finally the mutation rate is adapted accordingly. The underlying idea is to couple the mutation rate increase factor to the severity of the change. The addition or removal of a deployment potentially has a greater impact. Therefore, in addition to re-staging and adapting the mutation rate, a portion of the current population is substituted by a randomly initialized one. In case of removal of a deployment, all individuals containing the related gene have to be replaced. If a change occurs in $OP(t)$, the objective weights are adjusted, the mutation rate is adapted, and the total number of generations is increased.

In order to efficiently reuse good solutions computed in past optimization runs, the concept of *Persistent Memory* (PM) for solutions is introduced. This memory stores each combination of abstract (input) workflow and $OP(t)$ with the timestamp TS of the last optimization run in that combination, and the computed Pareto solutions. This simple schema is depicted in Figure 6.4. This concept is different than the implicit and explicit memory approaches described in Section 6.2, because the memory is completely external to the algorithm, and persistently stored. Such an external memory can be realized for specific problems that have a central registry component that acts as natural candidate for hosting the PM. There are several possible change scenarios. First, if an incoming request has an input workflow WF, the active optimization profile is $OP(t)$, the combination $(WF, OP(t))$ exists in the memory, and the timestamp of the respective memory entry is greater or equal to the last system change timestamp, then the solution in memory can be directly used, and there is no need to run any optimization. If the scenario is similar except that $TS < last\_change\_TS$, i.e., a system change occurred in the meantime, an optimization is started, but only a portion of the population $P(0)$ is initialized randomly, and the other portion is populated with individuals from the last solution. Additionally, based on the change impact, the mutation rate is adapted. Here again, the case in which a deployment has been removed has to be treated separately, i.e., previous solutions containing this deployment cannot be considered. At the end of the optimization run, the memory is updated on the attributes `TS` and `last_generation`. If the $(WF, OP(t))$ pair does not yet exist in memory, the population is randomly initialized, and at the end of the optimization run a memory entry is created accordingly.

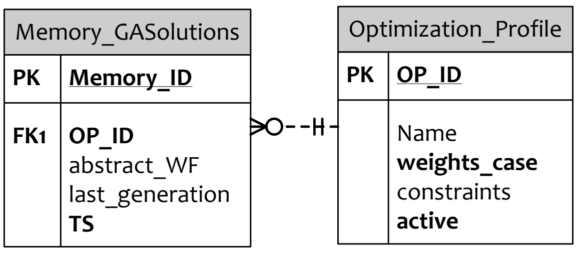


Figure 6.4: Schema of the Persistent Memory of Solutions

6.4.5 Integrated Optimization Approach with AD-MOGA

Figure 6.5 shows how AD-MOGA fits into the overall optimization process by summarizing and putting in relation all the required steps, from the input request to the actual deployment execution and logging. The stages in the process are the following:

Staging. During staging, the abstract workflow input is analyzed and the data needed for the optimization is loaded. This requires a connection to the central registry component that contains the services, deployments, links, their associated, up-to-date QoS attributes, and the active optimization profile. The latter one determines ranges for the objective weights. Additionally, changes since the last execution with a similar abstract input workflow are analyzed and assessed in order to determine the initialization method.

Optimization. The optimization stage refers to the execution of AD-MOGA itself. As described in Section 6.4.4, the exact mode of execution depends on the analysis of the dynamics carried out in the staging phase.

Decision and Execution. Per se, AD-MOGA returns a set of Pareto candidate solutions instead of a single solution that can be used right away for deployment composition. Therefore, in this model, an a posteriori decision has to be made with regards to the solution (workflow) to execute. Different approaches can be adopted. For example, the distance from the theoretical ideal point can be determined, and the nearest solution from this point can be chosen. Another approach is to randomly select a solution from a certain region of the Pareto set (for example from one region favoring one objective). In the same way as inside AD-MOGA, quasi-random weights can be computed and the best solution according to these weights can be determined. AD-MOGA is explicitly designed to keep this post-algorithm decision open, in order to allow for a greater flexibility of the approach, when applied to different scenarios. However, the decision can also be integrated into the algorithm itself, so that it returns only a single solution as output at the last generation.

Logging. Finally, the statistics on the deployment executions are logged into the Logging Component. These are then analyzed, aggregated and used to updated the central registry, thereby influencing the QoS values and thus the subsequent optimization runs.

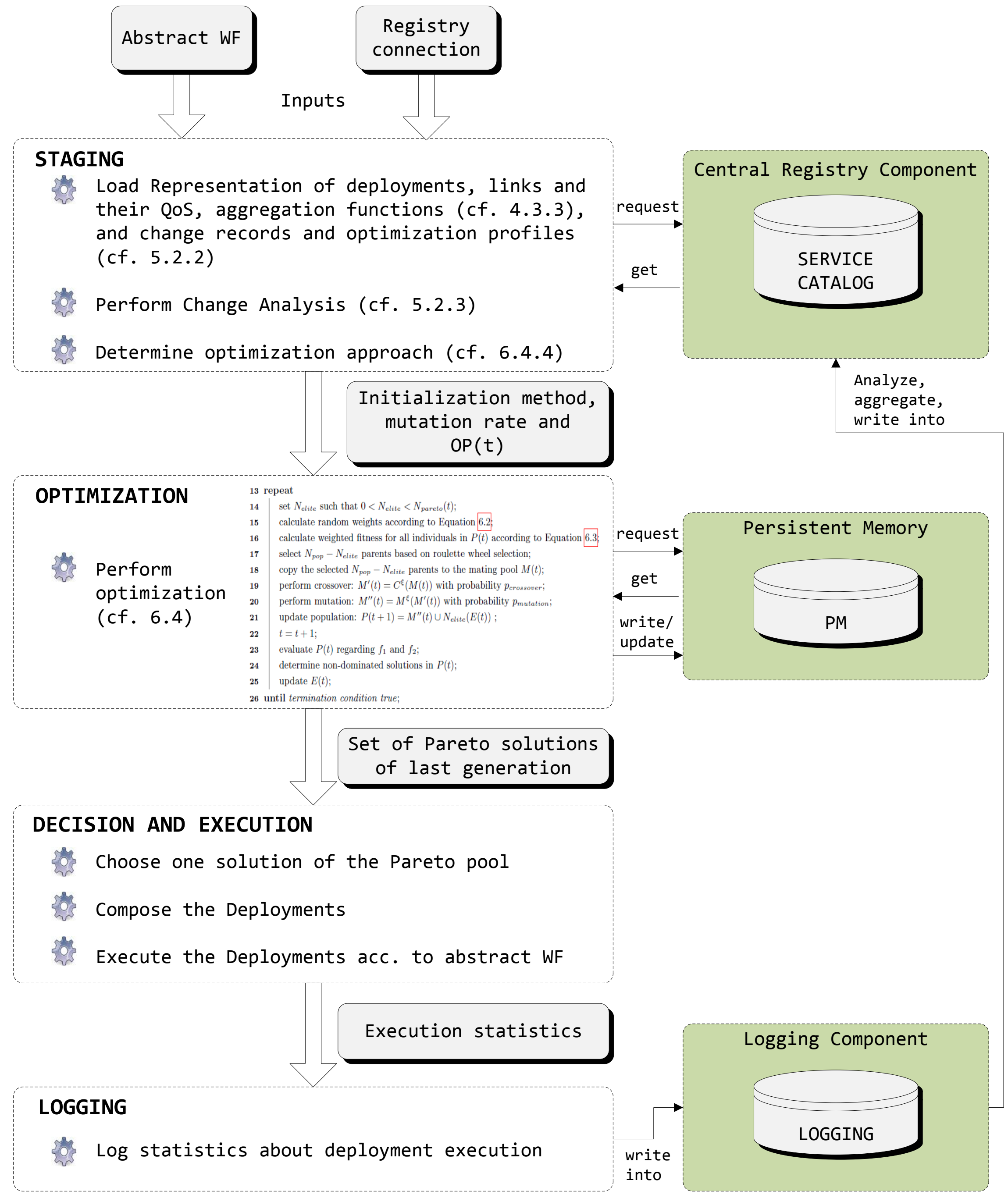
6.4.6 Tuning Possibilities

The efficiency of a GA (for a given problem size, encoding, and set of parameters) depends on the implementation of the genetic operators and on the resources on which the algorithm is executed. In order to speed up existing GA, several authors studied parallelization methods and proposed taxonomies of parallel GA models and implementations (e.g., [2, 21, 67]). Nowostawski and Poli [67] point out three main motivations to parallelize a GA:

- Some problems require a very large population that is highly memory-consuming and thus makes it impossible to efficiently run a sequential genetic algorithm on a single machine.
- Sequential genetic algorithms can get trapped in certain regions of the search space, and thus in local optima. Parallel algorithms however can search different regions in parallel and thus reduce the risk to return local optima.
- For complex problems, fitness evaluation can be very time-consuming. As the fitness has to be computed once for each individual, it is a natural candidate for parallel processing.

There exist several approaches for parallelizing a GA. The three main classes are briefly discussed in the following:

1. Distributed fitness evaluation (also called master-slave model) is a functional decomposition model [21], i.e., independent tasks are run concurrently, on multiple processors. The evaluation of the fitness for an individual only requires knowledge about the individual, and no global information on the level of the entire population. Therefore, fitness evaluation is a natural candidate for parallelization. It can be parallelized using a master-slave model. A master process distributes the evaluation of individuals to n slave processes and waits for them to return the computed fitness value. In a synchronous implementation, the master waits for all slaves


Abstract WF
Registry connection
Inputs
STAGING
Load Representation of deployments, links and their QoS, aggregation functions (cf. 4.3.3), and change records and optimization profiles (cf. 5.2.2)
Perform Change Analysis (cf. 5.2.3)
Determine optimization approach (cf. 6.4.4)
request
get
Central Registry Component
SERVICE CATALOG
Analyze, aggregate, write into
Initialization method, mutation rate and OP(t)
OPTIMIZATION
Perform optimization (cf. 6.4)
request
get
write/ update
Persistent Memory
PM
Set of Pareto solutions of last generation
DECISION AND EXECUTION
Choose one solution of the Pareto pool
Compose the Deployments
Execute the Deployments acc. to abstract WF
Execution statistics
LOGGING
Log statistics about deployment execution
write into
Logging Component
LOGGING

```
repeat
    set $N_{elite}$ such that $0 < N_{elite} < N_{pareto}(t)$;
    calculate random weights according to Equation 6.2;
    calculate weighted fitness for all individuals in $P(t)$ according to Equation 6.3;
    select $N_{pop} - N_{elite}$ parents based on roulette wheel selection;
    copy the selected $N_{pop} - N_{elite}$ parents to the mating pool $M(t)$;
    perform crossover: $M'(t) = C^{\xi}(M(t))$ with probability $p_{crossover}$;
    perform mutation: $M''(t) = M^{\xi}(M'(t))$ with probability $p_{mutation}$;
    update population: $P(t+1) = M''(t) \cup N_{elite}(E(t))$ ;
    $t = t + 1$;
    evaluate $P(t)$ regarding $f_1$ and $f_2$;
    determine non-dominated solutions in $P(t)$;
    update $E(t)$;
until termination condition true;
```

Figure 6.5: Overview of the Optimization Process

to return before continuing with the next steps of the algorithm. If an asynchronous model is chosen, the master can proceed after a fraction of the slaves returned, without waiting for the slowest processors. This changes however the behavior of the overall algorithm and it cannot safely be compared with its sequential equivalent. It has to be pointed out that the handling of the master and slaves processes introduces a communication overhead. Therefore, such a model is only profitable for problem settings with very complex fitness evaluation functions, in which the gain from parallel processing by far outweighs the introduced communication.

2. Island models constitute a data decomposition approach [21], i.e., the algorithm is concurrently evolved on different subsets of data. Typically, the population is divided into several subpopulations (also called islands), each containing a subset of the individuals. The algorithm is run on each island and each individual only competes with the other individuals belonging to the same subpopulation [67]. In order to converge towards a global solution, individuals from time to time have to be exchanged between subpopulations. For this process referred to as *migration* [67], several parameters have to be introduced: the migration rate, migration interval, migration scheme (defining which individuals are migrated: the best, the worst, random ones, etc.) and the topology (defining if individuals can migrate to any other subpopulation or only neighboring ones). Depending on the number of subpopulations and individuals per subpopulation, coarse-grained (few subpopulations with many individuals) and fine-grained (many subpopulations with few individuals) models are distinguished.

3. Hybrid methods combine ideas from the above-mentioned and other parallelization models. For example, subpopulations can be overlapping. In this case, no migration is defined between subpopulations, but individuals in overlapping regions can evolve in all of them. The spatial structure then defines the interaction between individuals [67]. If there are many of those overlapping subpopulations, each containing very few individuals, the algorithm is said to be *massively parallel* [67]. The spatial structure in which the individuals are placed is commonly a two-dimensional grid, but can also be a hypercube, for example. The ideal case is to assign one individual to each processing element as disposal. This technique can be used on massively parallel computers for very large problem settings requiring complex computations. Furthermore, subpopulations could be dynamic, self-adapting, etc., leading to new hybrid parallelization methods.

All of the above mentioned methods come with costs, be they related to the communication between processes, or to the need for new parameters that have to be determined properly. Therefore, the gain from parallelization in general and a specific method in particular, has to be evaluated per algorithm and problem setting. Additionally, the choice is dependent on the available hardware and computer architectures, because each method is best applied to a specific architecture. For example, coarse-grained island models map well to a multiple-instruction, multiple data stream (MIMD) model [2, 67]. Regarding the computational gain obtained with parallelization, Alba and Tomassini [2] propose different definitions of speedup. They point out that a parallel GA has to be compared with its exact sequential counterpart under identical conditions, which is not straightforward due to the stochastic nature of a GA. For example, the number of iterations studied in the sequential and the parallel case cannot be fixed because it can lead to solutions of different qualities. Rather, the stopping criterion of the parallel algorithm has to be such that the quality of the solutions is identical to the ones obtained with the sequential algorithm. Most of the parallelization methods will most likely not lead to a linear speedup function, but rather to a super-linear speedup followed by a negative speedup for a number of processes higher than a certain threshold. This in turn has to be determined per algorithm, platform, and problem setting.

Although a first and very basic approach for parallelizing a GA for the QoS-aware service selection problem has been studied by the author and P.P. Beran in [13], it is argued that the rather small problem settings encountered in realistic scenarios and the relatively inexpensive fitness functions do not make parallelization a very promising direction. However, in the context of scalability studies, in which AD-MOGA is applied to very large (simulated) problem spaces, parallelization can be a future research direction.

6.5 Related Work

In this section, closely related work on applying multi-objective GAs to QoS-aware service selection problems is surveyed. The main references and algorithms proposed are described, and the applied concepts and methods are summarized in Tables 6.3 and 6.4. The algorithmic contribution of this thesis presented in Section 6.4 builds on the knowledge gained from those related works, and extends them as aforementioned.

Canfora et al. [22] seem to have been the first to propose the use of GAs for solving QoS-aware service selection problems specifically. The authors define several QoS attributes and their aggregation functions, and a single-objective fitness function including costs, response time, availability and reliability, and respective weights. They enable constraint handling by introducing a distance-based penalty function reflecting the distance from constraint satisfaction. This distance measure is also part of the fitness function, and its weight can either be static or dynamically increasing, in order to allow potentially good solutions, but violating the constraints, in the early generations. The selection is based on roulette wheel, and crossover and mutation probabilities are fixed to 0.7 and 0.01 respectively. The elitist strategy used is to keep the two best individuals across generations. The authors perform simulations and compare their approach to integer programming. They conclude that their GA outperforms integer programming when the number of deployments per service exceeds 17, in their specific setup. For small systems, integer programming is the preferred approach.

Jaeger and Mühl [52] extend the work presented in [22]. They use the same QoS values and fitness functions and analyze the impact of varying the mutation probability, the number of generations, the structure of the fitness function and the penalty factor. Their simulations determine good values or value ranges for these factors. These values are however specific to the exact implementation of the algorithm. Additionally, they compare the GA to an exhaustive search, a branch-and-bound and a local hill-climbing approach, in terms of the QoS value reached. While the exhaustive search and the branch-and-bound algorithm do not perform in reasonable time in large problem settings, they are used to determine the optimal QoS value. The GA proves to have a capability superior to the hill-climbing, but it does not reach 50% of the optimal QoS value. This is a surprising result, as also pointed out by the authors, but there is no further investigation.

Li et al. [60, 61] applied two existing GA, with small modifications, to the QoS-aware service selection problem. In [60], the authors evaluate the application of the Strength Pareto Evolutionary Algorithm 2 (SPEA2), presented in [110], to the service selection problem. They carry out a series of simulations with 4 services having 90 to 500 deployments each. Results show that SPEA2 is able to guide the search towards the Pareto front. The input parameters to the algorithm are provided, but no explanation is given about how they have been determined. Additionally, questions about specific behavior are left open, for example why the algorithm converges quicker when each service has 500 deployments compared to 200. Only sequences of services are considered in this paper. The SPEA2 algorithm is outlined in Algorithm 6 [110]. In [61] Li et al. apply the Nondominated Sorting Genetic Algorithm II (NSGA-II) algorithm, proposed in [33], to the service selection problem. Simulation runs for two different setups are carried out, one with 4 services having 90 deployments each, the second one with 12 services having 30 deployments each. Results show that in both settings the number of non-dominated solutions increases approximately at the same rate, suggesting that NSGA-II distributes the solutions well on the Pareto front. The NSGA-II procedure is outlined in Algorithm 7. The author's plan is to compare SPEA2 and NSGA-II in QoS-aware service selection environments in a future work project.

Earlier, Claro, Albers and Hao [29] suggested using NSGA-II for the same kind of problem. In their simulations, they assessed the quality of the results as well as the scalability of the approach. The authors show that feasible Pareto-optimal solutions are found, and an increasing number of populations is needed with increasing problem setup, i.e., number of services and tasks.

Algorithm 6: SPEA2: Strength Pareto Evolutionary Approach 2

```
1  *Pop*: Population size;
2  $\overline{N}$: Archive size;
3  *maxGen*: Maximal number of generations;
4  Initialize Population $P(0)$;
5  Create empty Archive $\overline{P}(0)$;
6  $t = 0$;
7  **repeat**
8      Compute Fitness of Individuals in $P(t)$ and $\overline{P}(t)$;
9      Copy all non-dominated solutions from $P(t)$ and $\overline{P}(t)$ to $\overline{P}(t+1)$;
10     **if** *size($\overline{P}(t+1) \geq \overline{N}$)* **then**
11         reduce $\overline{P}(t+1)$ by specific truncation operator;
12     **else**
13         Fill $\overline{P}(t+1)$ with dominated solutions from $P(t)$ and $\overline{P}(t)$
14     **end**
15     Binary Tournament Selection to fill the Mating Pool;
16     Apply crossover and mutation;
17     $t = t + 1$
18 **until** *termination condition true*;
```

Liu et al. [62] were among the first ones to suggest the use of a multi-objective GAs to solve the service selection problem modeled as a multi-constraint multi-objective optimal path problem. Their proposed algorithm, named *Global Optimization of Dynamic Web Services Selection* (GODSS), is listed in Algorithm 8. The objectives, as described by the authors, are to minimize costs and execution time of a workflow, while having constraints on reputation and reliability. No evaluation

Algorithm 7: NSGA-II: Non-Dominated Sorting Genetic Algorithm-II

```
create initial population;
repeat
    fastNonDominatedSort;
    crowdDistanceSort;
    nonDominateSelect;
    crossover;
    mutate;
    for $i = 1$ to popSize do
        for $j = 1$ to NumOfObjectives do
            computeFitness(i,j);
        end
    end
until termination condition true;
```

of the algorithm is carried out.

Algorithm 8: Global Optimization of Dynamic Web Services Selection (GODSS)

```
Produce a set of initial feasible composition paths.;
Produce initial population (fixed-length-integral coding);
repeat
    Fitness Assignment (Pareto-based) and maintenance of diversity (based on entropy theory);
    Elitism (keep non-dominated solutions);
    Selection (Roulette Wheel);
    Crossover;
    Mutation;
    Yield new population;
until termination condition true;
Output: set of Pareto-optimal composition paths;
```

An interesting approach for addressing the QoS optimization of Grid workflows is presented by Tong, Cao and Zhang [80]. Starting from the observation that a Grid environment is composed of independent domains, they propose a distributed GA, where the population is divided into subpopulations, and each subpopulation is evolved at a domain. According to predefined migration interval and rate, individuals from the Pareto set of each subpopulation are migrated to a neighboring subpopulation, replacing the worst two individuals there. This communication mechanism between subpopulations can be considered as an implicit elitism. This distributed GA, outlined in Algorithm 9, can easily be parallelized, which allows reducing its overall computation time. Experiments have been conducted in a setup involving 16 abstract services having 32 deployments each, 10 domains (subpopulations) and 50 individuals per subpopulation. The objectives are to minimize overall costs and execution time, while meeting constraints imposed on reliability, reputation and security. Results show that the Pareto set converges after about 100 generations, and that the two objectives are really independent. No conclusions regarding the computation time and no comparisons to other approaches are made. The authors point out that in their paper the QoS values are assumed static, and future work would involve considering dynamics inherent in a Grid environment. However, surveying the existing literature, it seems that no such work has been presented yet.

Algorithm 9: Distributed Multi-Objective Genetic Algorithm by Tong et al. [80]

```
1  Generate initial population randomly;
2  Divide the initial population into $n$ subpopulations;
3  Evaluate the individuals according to fitness function;
4  repeat
5      Binary tournament selection ;
6      Crossover and Mutation;
7      Evaluate the individuals according to fitness function;
8      if Migration condition then
9          Perform migration and evaluation
10     end
11 until termination condition true;
```

The work of Wada et al. [90, 92] is close to the approach presented in this thesis. In [90], the authors introduce E^3-MOGA, a multi-objective genetic algorithm that considers multiple service level agreements (based on QoS) simultaneously and optimizes service compositions. It outputs a set of Pareto-optimal solutions as trade-off, and the final decision is up to the user. The considered QoS attributes are throughput, latency and cost, and overall qualities are defined at three levels, platinum, gold and silver. The authors start from the assumption that probability distributions of QoS measures can be determined based on the analysis of historical data. They conducted simulations with four abstract services having three deployments each, at different QoS levels, showing the applicability of E^3-MOGA. Recently, the authors extended their work in several ways to address deployment optimization in cloud computing environments [92]. Here, queuing theory is leveraged to predict the throughput and latency of atomic and composite services. Additionally, the authors propose an objective reduction mechanism that allows identifying redundant objectives and thus reduce the number of them. Indeed, in optimization problems with more than three objectives, solutions tend to be non-dominated, i.e., it is rare to find solutions that are better than others regarding all objectives. The presented overall optimization algorithm is referred to as E^3-R. Is is built on E^3-MOGA as described above, leveraged by mechanisms to predict deployment performance and to reduce the number of objectives.

Wang and Hou [93] present a QoS-aware service selection problem taking into account three objectives (minimization of the costs, minimization of the response time and maximization the reliability), three control structures (sequence, parallel, choice), and inter-services constraints (alliance, competition or no relation between services). They use a binary encoding and propose a multi-objective GA with selection based on Pareto ranking, one-point crossover and elitism. Experiments conducted with a total of 35, 70 and 105 deployments in total show that the algorithm reaches 91%

of the optimal values for all three QoS measures.

The methods employed in AD-MOGA and in the related work described in this section are summarized in Tables 6.3 and 6.4. It can be seen that none of the closely related work is considering the dynamic aspects of the underlying system. This thus constitutes a contribution of this thesis.

6.6 Summary

Genetic algorithms can be used to solve both single- and multi-objective QoS-aware service selection problems. When designing multi-objective GA, specific design considerations have to be taken into account, mostly in order to ensure that diversity of the population is kept across generations and thus prevent the algorithm from converging towards a local optimum. In the literature, several works are found that deal with the direct application of multi-objective GAs to QoS-aware service selection problems. However, none of the presented GA-based approaches allows the representation of general flow structures, and the explicit consideration of dynamics encountered in the underlying system made up of services, resources and deployments. To bridge this gap, an adaptive and dynamic multi-objective GA, referred to as AD-MOGA, has been introduced in this chapter. It allows taking into account optimization profiles (as defined in Chapter 5) through the use of random weights assigned within predefined ranges. These random weights also ensure that diversity is kept in the population of the GA. It further makes use of an explicit, persistent storage of good solutions from previous optimization runs to ensure a good initial population, and implements an adaptive mutation rate depending on the impact of system changes. The next chapter presents the evaluation results of this approach.

Reference	Encoding	Operators	Fitness	Diversity	Elitism	Constraints	Dynamics
[22, 52]	Integer	2-points crossover, Roulette wheel selection	Single-objective	n/a	Yes	Distance-based penalty	No
[60, 110]	Integer	1-point crossover, Binary tournament selection	Pareto-dominance and density	Fitness sharing	Yes, in extra list	n/a	No
[61, 29]	Integer	Binary tournament selection	Non-dominated sorting	Crowding distance	Yes	Penalty function	No
[62]	Integer (fixed-length)	2-points crossover, Roulette wheel selection	Pareto sort	Information entropy	Yes	Death penalty	No

Table 6.3: Comparison of Approaches to QoS-Aware Service Selection with GA (1)

Reference	Encoding	Operators	Fitness	Diversity	Elitism	Constraints	Dynamics
[80]	Integer	Crossover not implemented, Binary tournament selection	Domination rank	n/a	n/a	Penalty function	No
[90]	Integer (fixed-length array)	Roulette wheel selection	Domination rank and density	Cell-based density	Yes	Penalty function	No
[93]	Binary string	1-point crossover	Pareto-ranking	No	Yes, inside the population	No	No
AD-MOGA (this thesis)	Special reference encoding (cf. 6.4.1)	1-point crossover, Roulette wheel selection	Pareto-based, random weights	Random weights	Yes, inside the population	Death penalty	Yes

Table 6.4: Comparison of Approaches to QoS-Aware Service Selection with GA (2)

Chapter 7

Implementation and Evaluation

This chapter presents and discusses the evaluation results of the optimization approach proposed in Chapter 6. The evaluation of AD-MOGA focuses on three quantitative aspects. First, the “base” multi-objective GA underlying AD-MOGA is evaluated regarding its convergence, its approximation of the Pareto front and its diversity preservation. The “ideal” input parameters such as the mutation and cross-over rate are also investigated. Second, the behavior of AD-MOGA is simulated in a dynamic environment and its adaptability to changes is evaluated. Third, the algorithm is run on increasing problem spaces, with the aim of evaluating its runtime performance and scalability. Furthermore, a qualitative assessment is carried out. In particular, the integration of AD-MOGA into the TAG system is shortly discussed. In fact, most of the steps described throughout this thesis have been applied to the concrete TAG system. Therefore, experience could be gained regarding the design, implementation and integration of a deployment selection optimization framework into a real system. Especially when started from scratch, it is a long process that allows gaining deeper understanding of the underlying distributed system, beyond the initial scope, but also has drawbacks on the way.

This chapter is organized into sections as follows. Section 7.1 details the environment and setup used for simulation and evaluation of the proposed GA. Section 7.2 discusses the general applicability of AD-MOGA to service selection problems, and shows to what extent the algorithm approximates the Pareto front. In Section 7.3 the results of the evaluation of AD-MOGA regarding accuracy, stability and reaction capability are presented and discussed. The evaluation results of the runtime performance as well as the scalability of AD-MOGA with increasing problem spaces are presented in Section 7.4. The subsequent two sections specifically deal with the TAG system. Section 7.5 discusses the integration of AD-MOGA into the deployment selection optimization inside the TAG system. In Section 7.6 the experience gained while implementing a deployment selection optimization framework in a concrete distributed system is reflected, outlining the gains in terms of reached goals, as well as the drawbacks. Section 7.7 highlights possible enhancements and extensions for future work. Finally, the chapter is summarized in Section 7.8.

7.1 Simulation and Evaluation Setup

Although the approach is motivated by a real-world application, a simulation and evaluation environment has been set up. The reasons for this are manifold. First, simulation runs are computationally expensive and should not be carried out on a real-world production system. Second, the approach is evaluated on different setups, with different data constellations, etc. which cannot be realized on the fly on a production system. Finally, for studying the scalability of the approach, the problem space has to be bigger than the current TAG production system. Therefore, a simple registry has been created on a separate database schema. The data model is depicted in Figure 7.1. It is simpler than the TASK service catalog presented in Chapter 4, but holds the key concepts needed for carrying out the deployment selection, namely services, deployments, links and related attributes such as performance and usage indexes as well as other QoS metrics.

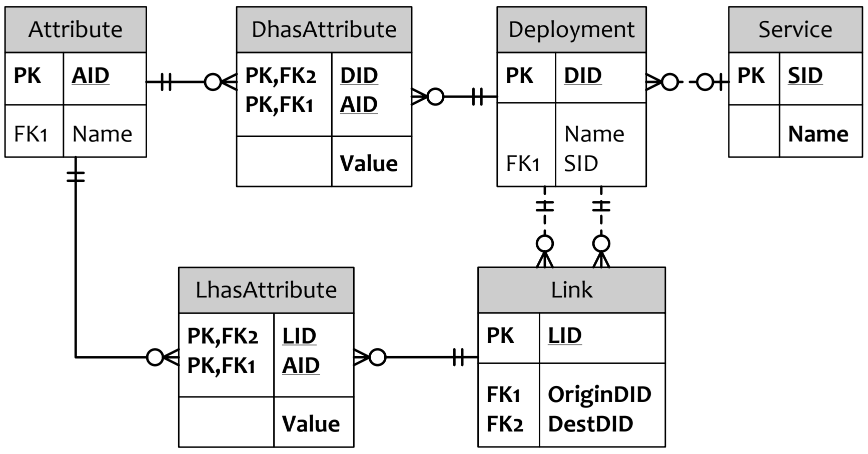


Figure 7.1: Simulation Setup: Database Schema

The tables are deployed on a development Oracle database hosted at CERN. AD-MOGA is implemented in Python and interacting with the database through *SQLAlchemy* [64], a Python SQL toolkit and object-relational mapper. The implemented classes are as shown in Figure 7.2. The class `System` captures the environment, that is the available system components and their attributes. These are loaded from the database via the `utils` package that uses the class `DBConnectionHandling` to interact with the central QoS repository. The components and their associated attributes are internally represented in Python dictionaries and queried throughout the optimization process. An instance of the class `GeneticAlgorithm` is created to start the optimization. It implements all the methods needed to evolve the population, such as `getFitness()`, `mutate()` and `crossover()`.

The algorithm is run locally. In order to be able to start simulation runs online and make use of a Cloud infrastructure, a related deployment selection simulation tool has been implemented on the Google App Engine [43]. The main goal of this joint work [13] with P. P. Beran (cf. Chapter 1, Section 1.4) was to compare a GA with a Blackboard approach on a common simulated problem setup. While the implementation of the optimization framework was straightforward and the comparison worked well for small problem settings, as expected it turned out not to be scalable for bigger simulation runs. This implementation thus had been considered as a proof of concept and has not been further investigated, nor used for the evaluation described in this chapter.

For carrying out the simulation runs, problem settings of different sizes have been created. The database schema presented above is populated using SQL and Python scripts, to which the total number of services and the number of deployments for each service are provided as input. Attribute values are randomly generated within predefined ranges. All simulation runs are based on at least 20 distinct experiments independent of each other.

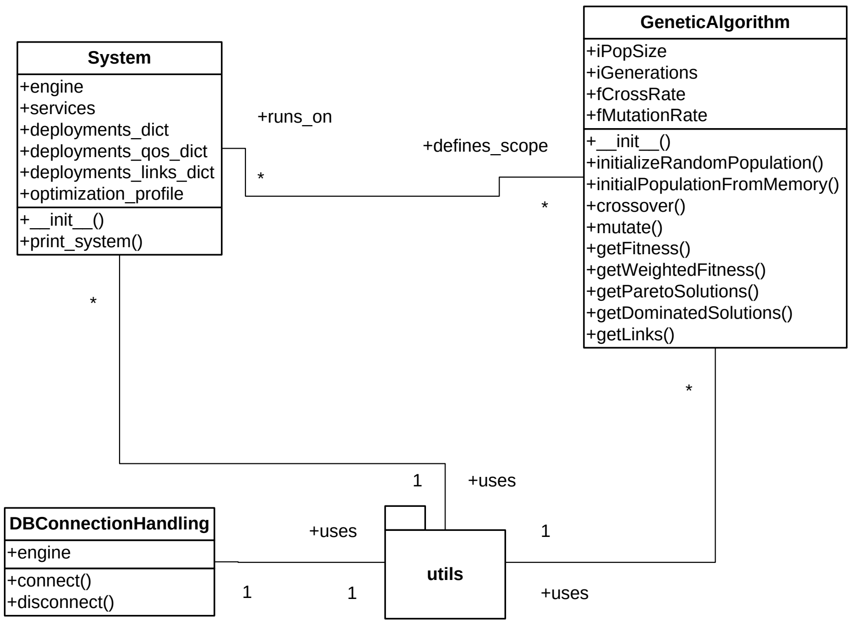


Figure 7.2: Classes and Packages in the Prototype Implementation

7.2 Evaluation Scenario I: Applicability of AD-MOGA, Pareto Approximation and Input Parameters

The first series of simulation runs aims at evaluating the ability of AD-MOGA to approximate the Pareto front (cf. Chapter 5, Section 5.4.2). For small problem setups, an exhaustive search algorithm has been run to determine the real Pareto solutions, and it has been verified that the solutions found with AD-MOGA are identical to those of the exhaustive search, and thus that AD-MOGA reaches the Pareto front. For bigger problem setups however, the exhaustive search could not be run on custom hardware, due to a lack of memory. It cannot be assumed that AD-MOGA *reaches* the Pareto front for large setups, but since its principal convergence has been demonstrated, it can be assumed that it *approximates* the Pareto front. The results of AD-MOGA, after a certain number of generations, are thus referred to as *Pareto candidates*. The test runs have been configured such that the Pareto candidates are also logged for a high number of generations, e.g., 500. It cannot be guaranteed that the result after 500 generations is the real Pareto front, but it can be considered as a fair approximation.

The first simulation runs have also been used as "calibration" regarding the input parameters, namely the population size, and the crossover and mutation rates. The following parameters lead to the most promising results:

- Population size: 100
- Crossover rate: 0.65
- Mutation rate: 0.02

However, it has to be pointed out that the *optimal* size of the population is dependent on the problem size. For small setups e.g., with 5 to 10 services having on average 5 deployments each (i.e., a realistic size of the TAG application system), a population comprising 50 individuals is big enough to show a good convergence towards the Pareto front at generation 100. But for these first test series the population size has been fixed at 100 in order to maintain the same parameters through the 6 runs.

The following simulation runs have been carried out with an even deployment distribution:

- Run 1: 5 services, 5 deployments each, workflow of 5 services, no constraints.
- Run 2: 5 services, 20 deployments each, workflow of 5 services, no constraints.
- Run 3: 10 services, 5 deployments each, workflow of 10 services, no constraints.
- Run 4: 10 services, 20 deployments each, workflow of 10 services, no constraints.
- Run 5: 20 services, 5 deployments each, workflow of 20 services, no constraints.
- Run 6: 20 services, 20 deployments each, workflow of 20 services, no constraints.

The following simulation runs have been carried out with an uneven deployment distribution (i.e., the services have different numbers of deployments):

- Run 1: 5 services, 100 deployments total (5-10-20-30-35), workflow of 5 services, no constraints.
- Run 2: 5 services, 100 deployments total (35-30-20-10-5), workflow of 5 services, no constraints.
- Run 3: 10 services, 200 deployments total (2-5-10-15-18-20-25-30-35-40), workflow of 10 services, no constraints.
- Run 4: 10 services, 200 deployments total (40-35-30-25-20-18-15-10-5-2), workflow of 10 services, no constraints.
- Run 5: 20 services, 400 deployments total (2-2-5-5-10-10-15-15-18-18-20-20-25-25-30-30-35-35-40-40), workflow of 20 services, no constraints.
- Run 6: 20 services, 400 deployments total (40-40-35-35-30-30-25-25-20-20-18-18-15-15-10-10-5-5-2-2), workflow of 20 services, no constraints.

Abstract workflows composed of 5 to 10 distinct services represent a reasonable scenario in real-world applications. Workflows containing 20 or more services, and each service having multiple deployments, are scenarios that can be used to test the scalability of an approach, but they are most likely not representative of concrete applications. In the TAG use case for example, there exist about 10 distinct services, and typical workflows do not involve all of them.

Figure 7.3 shows the results for the 6 simulation runs with even deployment distribution described above. Each plot represents the non-dominated solutions at different generations, namely generation 0 (random initialization), and the generations 20, 40, 60, 100, 300 and 500. Figure 7.4 shows the respective results for the 6 runs with uneven deployment distribution.

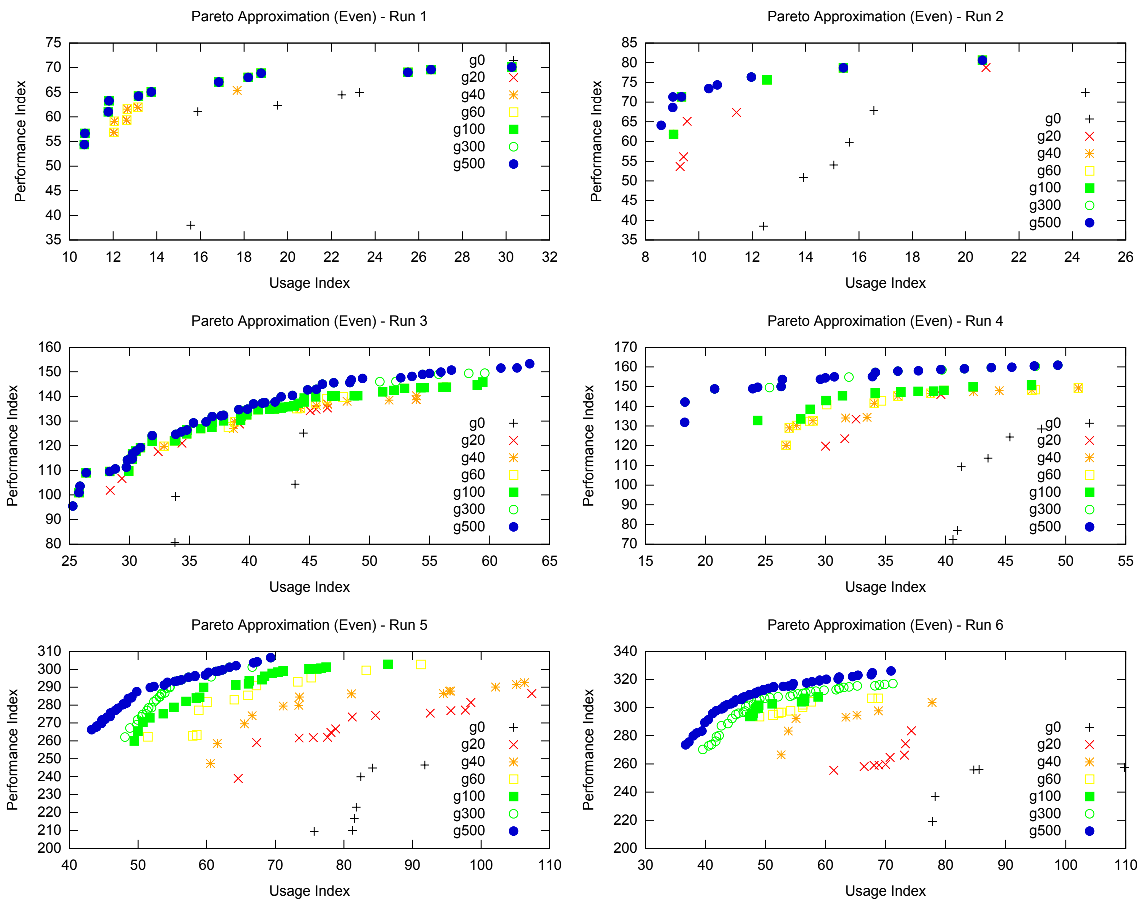


Figure 7.3: Approximation of the Pareto Front: Even Deployment Distribution

Figure 7.3 shows that for small system setups (Runs 1 to 3), AD-MOGA is converging after about 60 generations. For bigger setups (Runs 4 to 6), there are still small improvements between generation 300 and 500, but the Pareto candidates at generation 100 can be considered as a good approximation. It can also be seen that the algorithm makes a good approximation of the entire

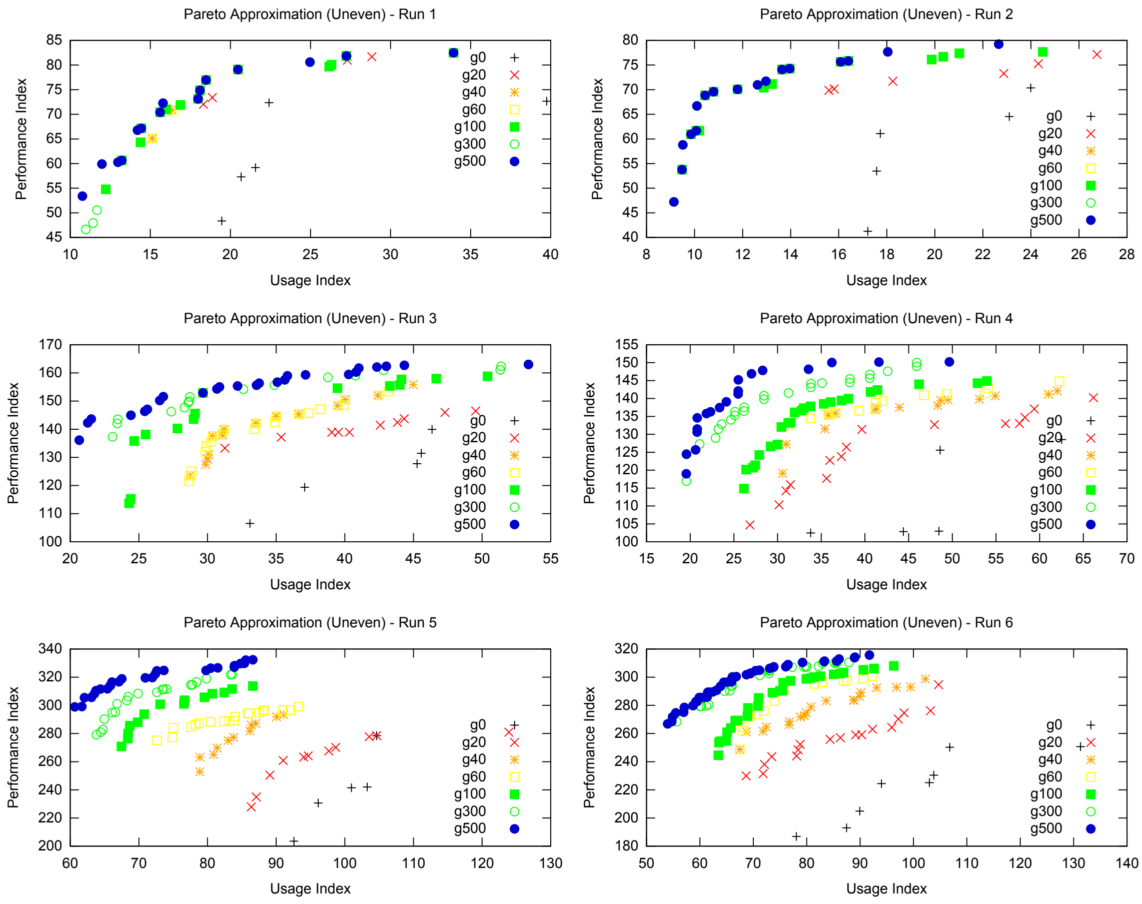


Figure 7.4: Approximation of the Pareto Front: Uneven Deployment Distribution

front, i.e., no genetic drift can be observed. Comparing Figure 7.3 and Figure 7.4, it can be noticed that in general the approximation converges faster for even deployment distributions. In rather "random" distribution scenarios, more generations are required to reach the Pareto front. This thus has to be considered when setting up the input parameters for the algorithm.

7.3 Evaluation Scenario II: Adaptability to Changes

7.3.1 Formal Evaluation Criteria for Dynamic GA

Evaluating the performance of an adaptive GA in a dynamic environment is more complex than evaluating a GA in a static environment, and special techniques are required. Weicker [96] summarizes three important measures in dynamic optimization: optimization accuracy, stability and reactivity. The *optimization accuracy* defines the quality of the best individual at time t compared to the overall best quality at time t. For the multi-objective case, this can either be computed by assigning weights to the objectives, thus reducing the problem to a single-objective one, or by calculating an average of the Pareto approximation. It is the same measure as the one evaluated in Section 7.2, with the difference that it is defined for a specific time t only. According to Weicker [96], an adaptive algorithm is called *stable* "if changes in the environment do not affect the optimization accuracy severely. That means that a stable, adaptive algorithm is required to be prepared for changes in the environment". The related metric is referred to as *stability*. Finally, the *reactivity* can be considered as a combination of accuracy and stability. It refers to the time needed to adapt to a change in the underlying environment. When evaluating a GA, this *time* can be measured in number of generations.

In the following subsections, these performance metrics are investigated for AD-MOGA, with the types of changes described in Chapter 6 (Section 6.4.4).

7.3.2 Implementation of the Persistent Memory

The "persistent memory" in which good individuals from past optimization runs are stored is integrated into the central QoS registry. As depicted in Figure 6.4 it is composed of a simple table that references the table storing the optimization profile. The granularity of the table is defined by the pair composed of the optimization profile ID (`OP_ID`) and the abstract workflow (`abstract_WF`). That is, for each such combination the latest generation or latest Pareto set of the last optimization run is stored, and a timestamp indicates the insert or update date of the entry. Figure 7.5 shows the sequence of actions when the memory is queried. First, the timestamp of the related memory entry is compared with all timestamps indicating system changes. When changes have occurred, they are first evaluated (i.e., the similarity index is computed) and then, based on the result of this index, the memory entry is retrieved or not. The update mechanism is similar. Each optimization run updates its corresponding memory entry, identified again by the (`OP_ID`, `abstract_WF`) pair. Or, if such an entry does not yet exist, it is inserted.

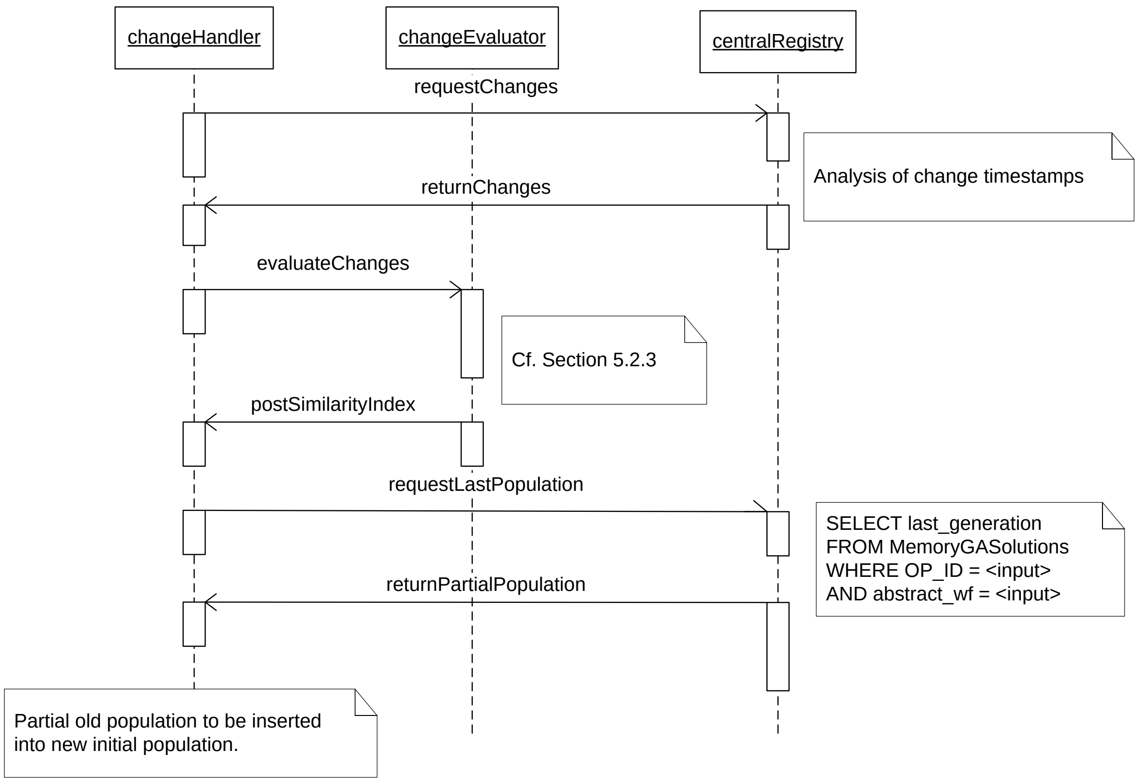


Figure 7.5: Schematic Query of the Persistent Memory

7.3.3 Changes During or Between Optimization Runs

In these test series, AD-MOGA is evaluated under the change conditions described in Table 6.2. (The scenario numbers also refer to those defined in Table 6.2.)

Scenario (4): $((WF, OP(t))$ in PM, and no system change. The pair composed of the abstract input workflow and the optimization profile exists in the persistent memory, and no change has happened since the last execution. In this case, no optimization has to be done because the previous solution can simply be reused. Therefore, the Pareto candidates stored in the PM are retrieved and passed on to the *Decision and Execution* stage of the optimization approach (cf. Figure 6.5).

Scenarios (1), (2) and (5): $((WF, OP(t))$ in PM, and non-radical system changes. To evaluate these scenarios, the following setup and steps are considered:

- System composed of 10 services having 5 deployments each (because this setup is closest to the reality of the TAG application scenario).
- Sequential workflow composed of 10 distinct abstract services.
- At time t, the system has a certain status: $SP(t)$ and $OP(t)$ as described in Chapter 5, Section 5.2. The GA is started for an abstract workflow W_0 and the Pareto candidates are evaluated as shown in Run 1 of Figure 7.6.

- At time $t + \Delta t$, there is a new request with the same workflow W_0 as input. Between t and $t + \Delta t$, the attribute value levels of two deployments of service 1, one deployment of service 2 and one deployment of service 3 have changed, as defined in Section 5.2. In a sequence of 10 deployments, there are 9 links, thus 19 components in total. According to Equations 5.6 to 5.9, and defining the three changed deployments as $D_1(S_1), D_2(S_2)$ and $D_3(S_3)$, this results in the following *similarity index*:

$$\begin{aligned}
imp_{C_i} &= \frac{1}{19} \\
si_{D_1(S_1)} &= \frac{1}{19} \cdot \left(1 - \frac{2}{5}\right) \\
si_{D_2(S_2)} &= \frac{1}{19} \cdot \left(1 - \frac{1}{5}\right) \\
si_{D_3(S_3)} &= \frac{1}{19} \cdot \left(1 - \frac{1}{5}\right) \\
si_{D_i} &= \frac{1}{19}, \quad \text{for } i = 4, ..., 10 \\
si_L &= \frac{1}{19} \cdot (9 - 0) = \frac{9}{19} \\
si_{total} &= \sum_{i=4}^{10} \cdot si_{D_i} + si_{D_1(S_1)} + si_{D_2(S_2)} + si_{D_3(S_3)} + si_L = \frac{91}{95} \quad \simeq \quad 0.958
\end{aligned} \tag{7.1}$$

  Therefore, overall the system is qualified as having "slightly changed" (cf. Figure 5.1).

- According to Table 6.2, the population is thus initialized with a fraction of the best individuals computed at time t, and the mutation rate is increased.

The plot for Run 2 in Figure 7.6 shows the convergence achieved using this technique. Concretely, the 18 individuals from the Pareto candidates computed in the previous optimization at time t have been inserted into the initial population, and the remaining 82 individuals have been initialized randomly. The mutation rate has been raised from 0.02 to 0.04. It can be seen that the algorithm converges rapidly without however losing its diversity range. As a comparison, Run 3 in Figure 7.6 depicts the convergence using a random initial population, similar to the one of Run 1. It can be concluded that in such a case the number of total generations can be reduced, thus reducing the total runtime of the algorithm. Alternatively, if another termination criterion is used (e.g., the number of new/changes Pareto candidates between generations), the algorithm will simply stop earlier.

Figure 7.7 shows the results for a similar test series as described above, but with more important changes between the optimization runs. Concretely, in this scenario changes were recorded on 10% of the components (deployments and links).

Figure 7.8 shows the results of a repeated similar test, but with a change rate of 50% (the change rate corresponds to one minus the similarity index). In this case, it can be seen that a restart with memory and a mutation rate of 0.05 present no advantage over a random initialization. Raising the mutation rate to 0.1 shows better results, which suggests that a gradual adaptation of the mutation rate as a function of the system change rate is a valid

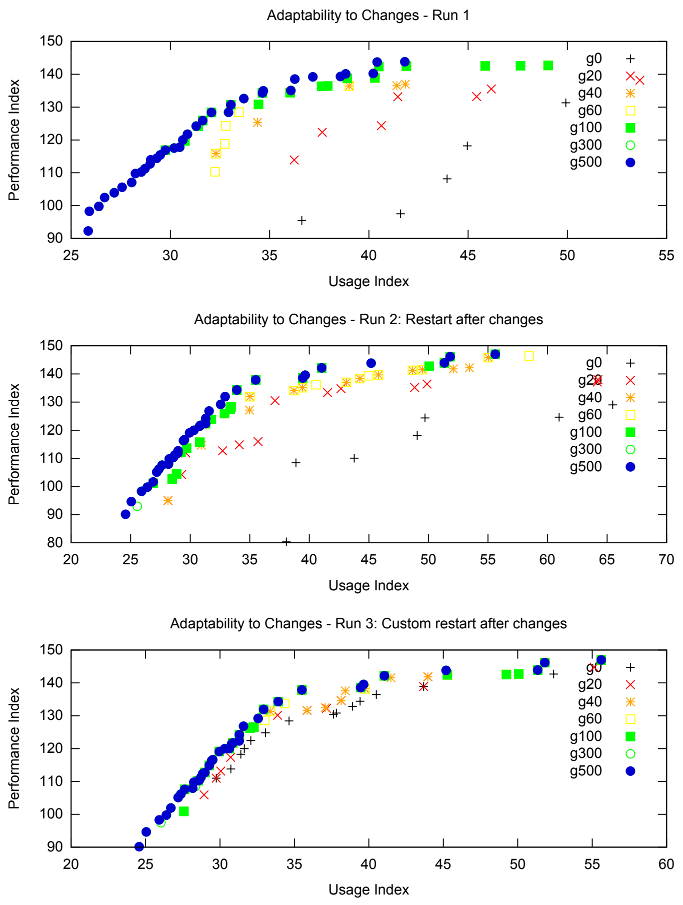
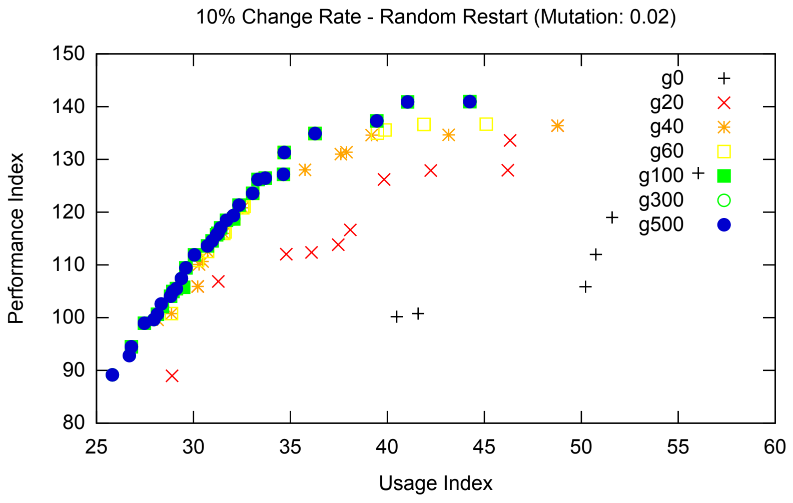


Figure 7.6: Changes Between Optimization Runs

strategy (this is discussed in more detail in Section 7.3.4.). However, compared to values used for the mutation rate in related literature on GAs, 0.1 is rather high, as the focus of a GA lies on the reproduction of fit individuals instead of random mutation. Overall, a system change rate approximating 50% can be considered as a threshold above which random restart is the preferred option.

Finally, another test series has been performed, in which an increasing number of deployments are added to the system after the last memory entry. Figure 7.9 shows the impact of adding deployments between optimization runs, by comparing random restarts with restarts from memory, for increasingly changing setups. This test series verifies the results discussed above, i.e., the similarity index is an appropriate measure for adapting the mutation rate, and for deciding on the algorithm initialization method. Here, a similarity index of about 0.6 (40% change rate) is the approximate threshold. In the experiment, the changes are performed randomly, i.e., attribute values are assigned randomly and no particularly good or bad solutions are introduced on purpose. Finally, it has to be mentioned that the disappearance of



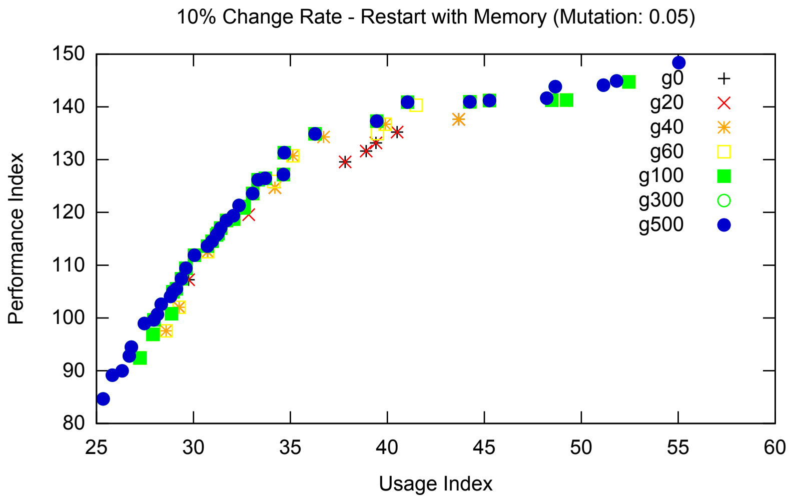


Figure 7.7: 10% Change Rate Between Optimization Runs

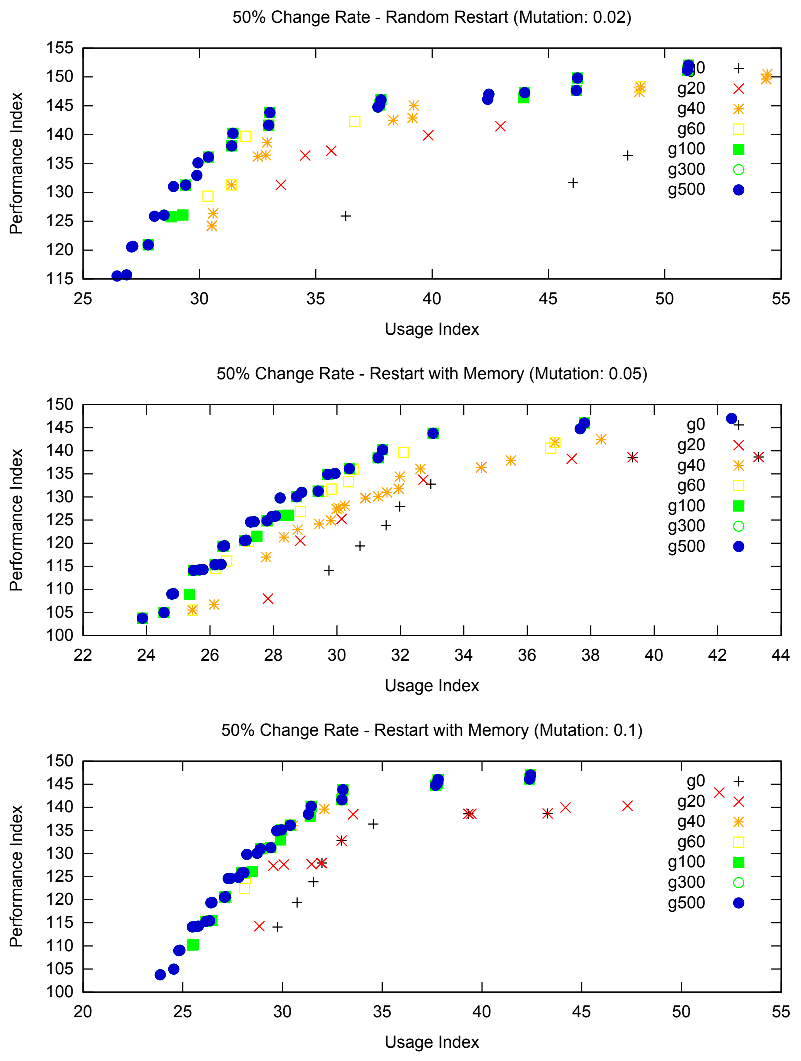


Figure 7.8: 50% Change Rate Between Optimization Runs

deployments has to be handled differently, as it invalidates previous solutions containing those deployments.

Scenario (3): Change in $OP(t)$. In this case, there is a change in the optimization profile during a run, i.e., the weights of the optimization objectives change, or constraints are introduced. In case a change in the weights is detected, several actions are taken: first, the fitness weighting is adjusted, second, if the new $(WF, OP(t))$ pair exists in memory, a fraction of the current population is replaced by individuals from memory, and the mutation rate is updated accordingly. Such changes are only assumed in long or continuously running optimizations. In case constraints are introduced, the constraint handling procedure is enabled from the current generation on.

Scenario (6): $((WF, OP(t))$ in PM, and radical change) OR $(((WF, OP(t))$ not yet in $PM)$. In this scenario, either the pair consisting of the abstract input workflow and the optimization profile does not yet exist in PM, or it does but a change categorized as *radical* has occurred since the latest related memory record. In such a case, the algorithm has to be restarted and the evaluation results presented in Section 7.2 are relevant.

In general, considering changes occurring *during* an optimization run is only sensible in case of a continuous optimization process. In this case, a separate process regularly queries the central registry to detect changes and signal them to the optimization process that then adapts to them, according to the change rate.

7.3.4 Stepwise Adaptation of the Mutation Rate

As suggested in Figure 7.8, it seems beneficial to adapt the mutation rate to the change rate. A few test series have been carried out to verify this assumption. An initial system comprising 10 services having 5 deployments each has been set up, an optimization run has been carried out and the Pareto solutions of the last generation have been saved into the persistent memory. Then, the system has been changed randomly in three subsequent steps, so that the optimization could be run on setups with decreasing similarity index, concretely 0.9, 0.8 and 0.7. For each of those changed setups, optimizations with increasing mutation rates have been run. Considered rates are 0.02 (and random restart), 0.03, 0.035 and 0.04 (restart from memory). The mutation rate is especially important in order to ensure diversity in the population after a change. The results are shown in Figures 7.10, 7.11 and 7.12.

For a similarity index of 0.9, the best results are achieved with the lowest mutation rate tested, namely 0.03. Augmenting the rate does not add diversity, nor lead to faster convergence – on the contrary, the convergence seems to be degrading for a higher mutation rate. For the next lower similarity index, 0.8, mutation rates of 0.03, 0.035 and 0.04 are almost equally good, no degradation is observed for a rate of 0.04. Finally, for the lowest tested similarity index, 0.7, the earliest convergence is achieved with the highest mutation rate, 0.04.

Adapting the mutation rate as a function of the similarity index thus seems to be a promising strategy. However, in order to derive a possible relation factor, many more experiments in varying system setups need to be performed. Additionally, a more fine-grained “zooming” into the population

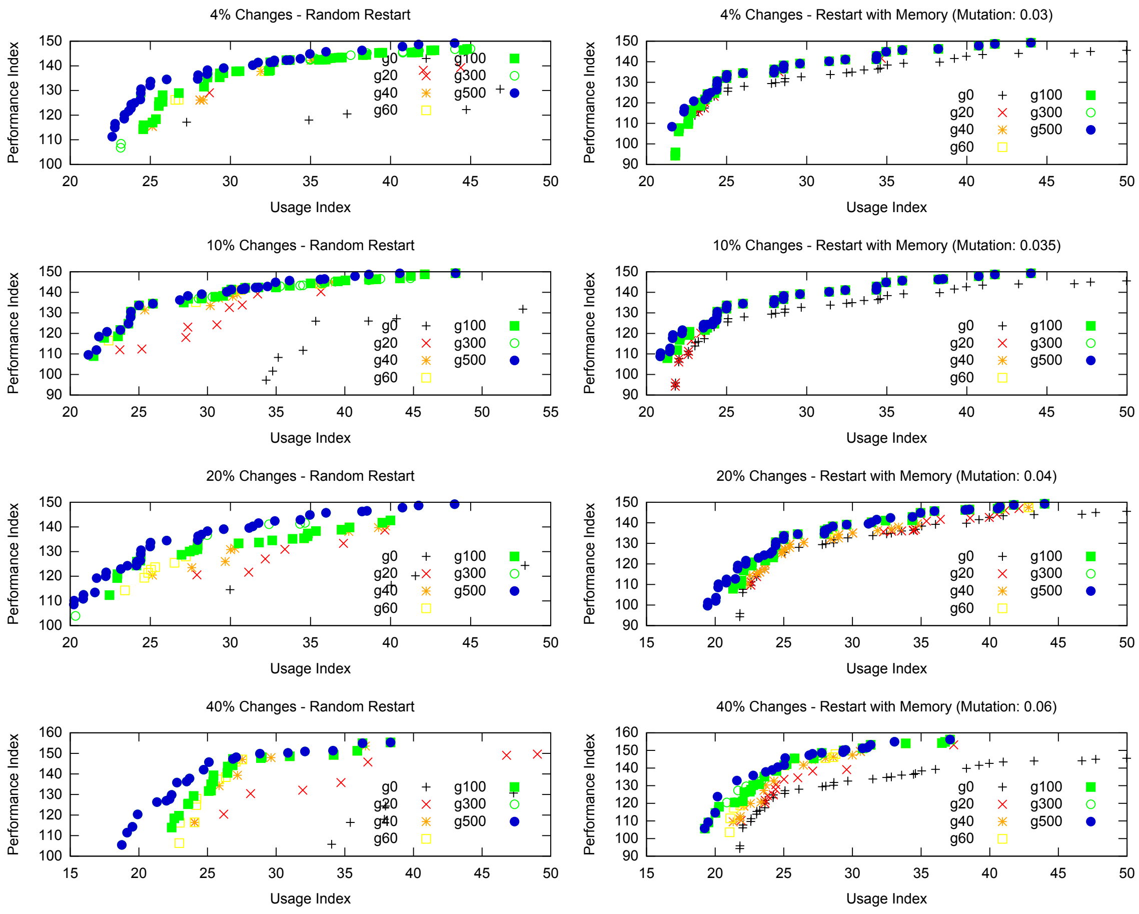


Figure 7.9: Impact of Adding Deployments with Different Change Rates

evolution needs to be carried out. A detailed analysis in this area represents a possible direction for future work.

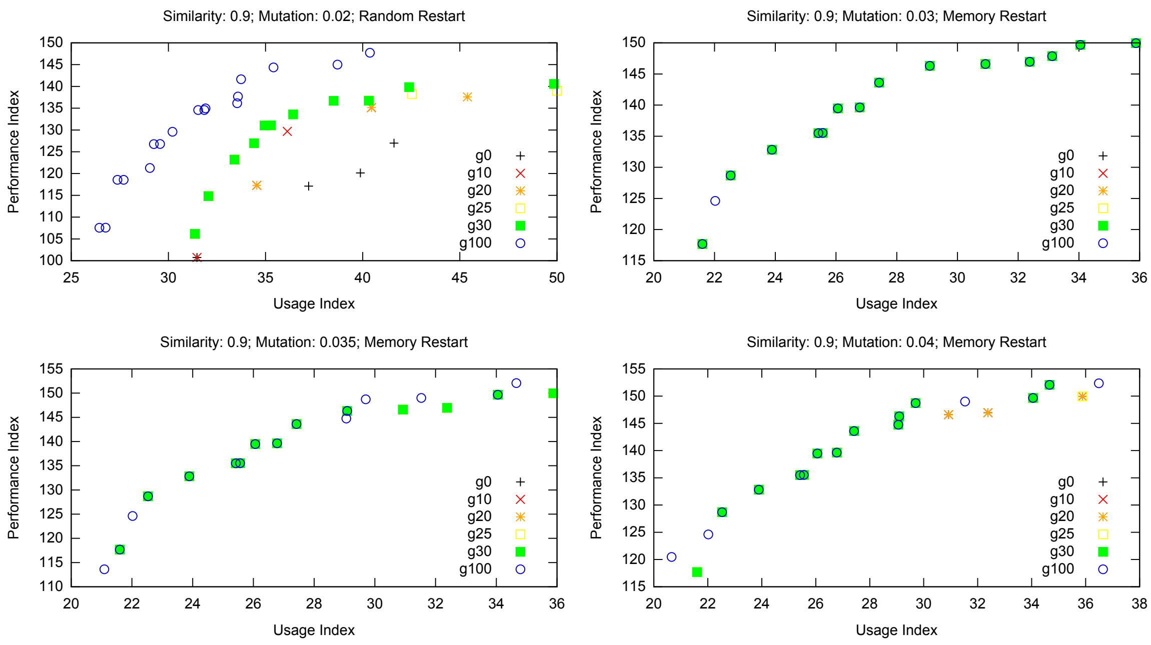


Figure 7.10: Impact of Varying Mutation Rates, Similarity Index 0.9

7.4 Evaluation Scenario III: Runtime Performance and Scalability

For the algorithm to be applied to a real system, it has to be tested in terms of runtime performance and scalability. In fact, if the time spent on the optimization is longer than the worst case execution time when a random or hard-coded composition is chosen, the approach is useless in a real environment. As suggested by the tests shown in Figure 2.7 (Chapter 2), in the concrete TAG system there is a rather large margin between the best and the worst combination – in this example timings are done for the composition of only two deployments, and it can be assumed that this margin increases with the length of the workflow. However, although this is not the primary focus in this evaluation, much consideration has to be put on the optimization of the algorithm itself, in terms of runtime. In order to do so, two tests have been carried out.

In the first test, the runtime and scalability have been assessed for an increasing number of services (thus an increasingly long workflow) and an increasing number of deployments per service. The results are displayed in Figure 7.13. One run has been made with 100 generations (because this setting produced a good Pareto approximation with random restart, cf. Section 7.2), another one with 50 generations (because this is the approximate number of generations needed with a start

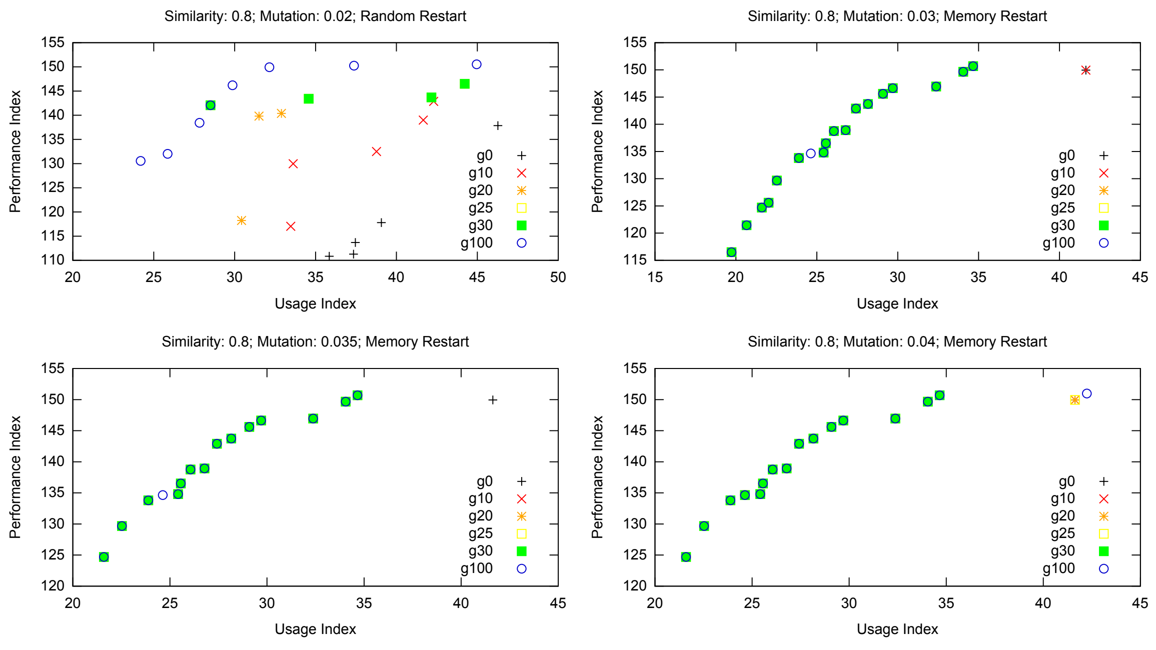


Figure 7.11: Impact of Varying Mutation Rates, Similarity Index 0.8

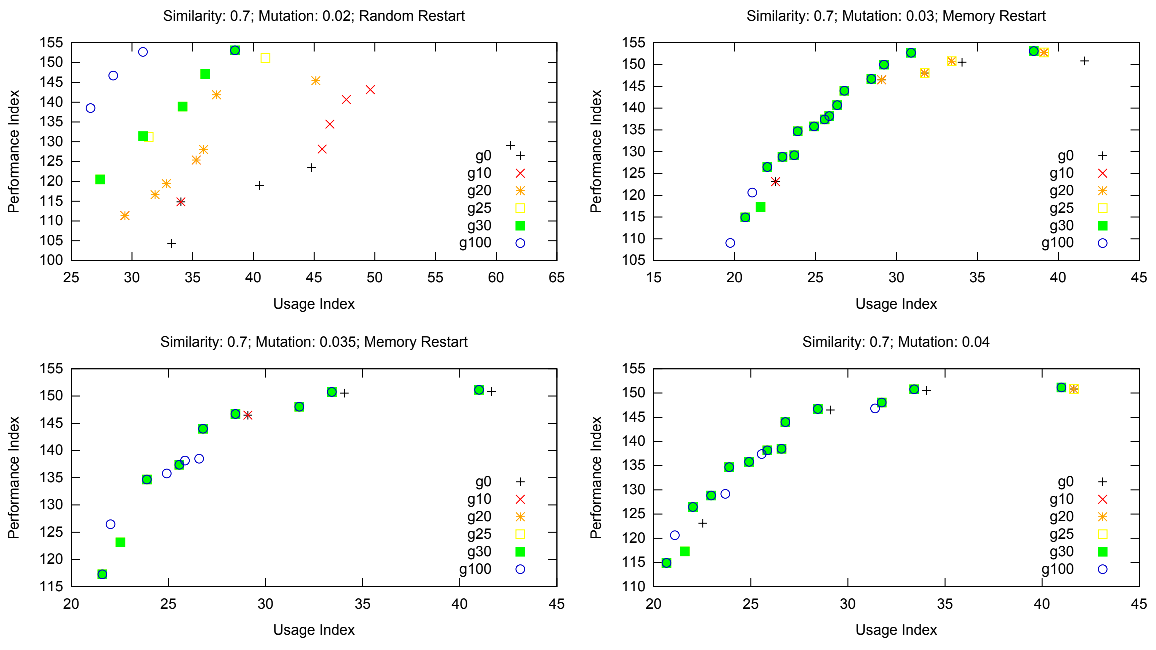


Figure 7.12: Impact of Varying Mutation Rates, Similarity Index 0.7

using memory, cf. Section 7.3). First, it can be seen that the runtime is relatively stable with an increasing number of deployments per service. This was mentioned as a motivation for using a GA (cf. Section 6.3). Second, evidently the runtime increases with the number of abstract services forming a workflow. In these test series, up to 30 deployments were defined per service. In real systems, this seems already a big number that is not likely to be reached. If it is however, in huge systems, an approach would be to form clusters of deployments presenting similar characteristics, then carry out the optimization based on those clusters, and finally choosing one deployment from the cluster. It also has to be considered that the allowed time to be spent on the optimization is highly dependent upon the time needed for the total workflow execution. For example, if the execution of five composed deployments takes 10 seconds in total, an optimization time of 10 seconds is hardly acceptable, except if the worst case time for the workflow execution is very different. If however the execution of the workflow is in the order of minutes, which is often the case of scientific workflows, an optimization time of the order of several seconds is clearly acceptable. In summary however, the runtime plotted in Figure 7.9 can be optimized, as pointed out in the following analysis.

In the second test, the total runtime is split into its main "components," i.e., the time needed to perform certain operations is logged separately. Concretely, the following times are put in relation: the time for querying the central registry – i.e., the time for connecting to the database, loading all the deployments of the required services and loading all the links, as well as their related QoS attributes (*Database time*), the time for computing the fitness of the individuals (*GetFitness time*), the time for determining the Pareto solutions (*GetPareto time*) and the total time. The same setup as in Run 2 from Figure 7.13 has been used. The remaining time, i.e., the total time minus the other mentioned ones, are spent on other operations such as initialization, mutation, crossover, etc. The results for 5, 10 and 20 services are displayed in Figure 7.14. In small systems (5 to 10 services), the largest part of the optimization is spent on the determination of the Pareto candidates. In the AD-MOGA prototype, the Pareto candidates are determined by comparing each individual with all the others. It is clear that this does not scale well and can be improved, specifically by implementing non-dominated sorting to avoid unnecessary comparisons. By doing so, the base algorithm would be close to the NSGA-II algorithm [33]. The time spent on the computation of the Pareto set is stable, because it only depends on the number of individuals per generation, i.e., the number of solutions to be compared. The run with 20 services in Figure 7.14 suggests that for bigger setups, the time spent for querying the registry represents an important fraction of the total time. In fact, the time for querying and loading the deployments and links is expected to be proportional to the number of deployments and links in the considered system (and part of the workflow), unless optimization approaches are carried out on the database side (e.g., by creating appropriate indexes on the required tables in order to speed up the queries).

In general, it has to be noted that in the performed test series the execution time is bound by the fixed number of generations. In fact, the time for fitness computation and the time for determining the Pareto candidates are stable throughout the tests, because they mainly depend on the number of individuals in the population. The time for computing the fitness further depends on the workflow structures (number of occurring patterns and their respective attribute aggregation functions), but here only sequences are tested. The only varying time is thus the database time, but many techniques exist for speeding it up, such as caching, index creation, and optimizing the database structures to accommodate larger datasets (e.g., partitioning, etc.). Therefore, all three specified time fractions are stable with regards to an increasing number of deployments per service and increasingly long workflows. However, two other factors influence on the runtime performance and scalability: the population size and the number of objectives. They are not concretely studied here, but briefly discussed in the following. For a fixed workflow length, the number of potential solutions increases exponentially with an increasing number of deployments per service. Considering a workflow of y distinct services and x deployments per service, the number of solution candidates is y^x (in the absence of constraints all candidate solutions are feasible). The adaptation of a GA to an increasing search space is achieved by adapting two parameters, namely the number of generations and the population size. Indeed, while a population size fixed at 100 contains a considerable subset of the individuals (namely $\frac{4}{25}$) when there are 5 services having 4 deployments each ($5^4 = 625$ candidate solutions), it is only a very small subset (namely $\frac{1}{1000}$) if 5 services having 10 deployments each are considered. Therefore, instead of adapting only the number of generations (and risking the loss of diversity), the population size can also be adapted with increasing search spaces. In terms of computational complexity, this affects the *GetFitness time* and the *GetPareto time* (both proportional to the number of individuals that have to be evaluated). On the other hand, the same convergence rate could then be achieved in fewer iterations. There is thus a tradeoff between those two parameters. To address the general issue of choosing an appropriate population size, self-tuning GAs have been proposed, e.g., in [76]. Another aspect that needs some consideration is the number of objective functions in a given problem. An increasing number of objectives influences both the *GetFitness time* (because more functions have to be evaluated, more weights assigned, etc.) and the *GetPareto time* (because the Pareto dominance has to be determined taking into account all objective functions). Non-dominated sorting has already been mentioned as a measure to improve the determination of Pareto candidates, by avoiding unnecessary comparisons. Regarding efficient fitness evaluation, one approach is to divide the population into subpopulations and to evaluate the individuals in one subpopulation on one objective, those in another subpopulation on another objective, and so on, in parallel. As in the parallel island model discussed in Chapter 6, Section 6.4.6, individuals then have to be migrated from one subpopulation to another, requiring the definition of additional parameters such as the migration rate and interval.

7.5 Application to the TAG System

AD-MOGA has been designed based on the analysis of the TAG system, in anticipation of a growth of the system. As described in Chapter 2, the system is composed of five sites and about ten services, so there is a potential for having 50 deployments in the system, if every service is deployed at each site. However, this is not yet the case, and the real production system currently has a smaller scope. It is expected to grow as more experiment data are taken, making the use of event-level metadata more and more beneficial to speed up physics analysis. Therefore, the use of the GA itself is currently not appropriate, but will be in future.

The main concept integrated into the real system is the service and QoS registry. The components of the *TAG Application Service Knowledge Base* (TASK) have already been described in Chapter 4, Section 4.4. The implemented parts include the data and service catalogs and their APIs, as well as

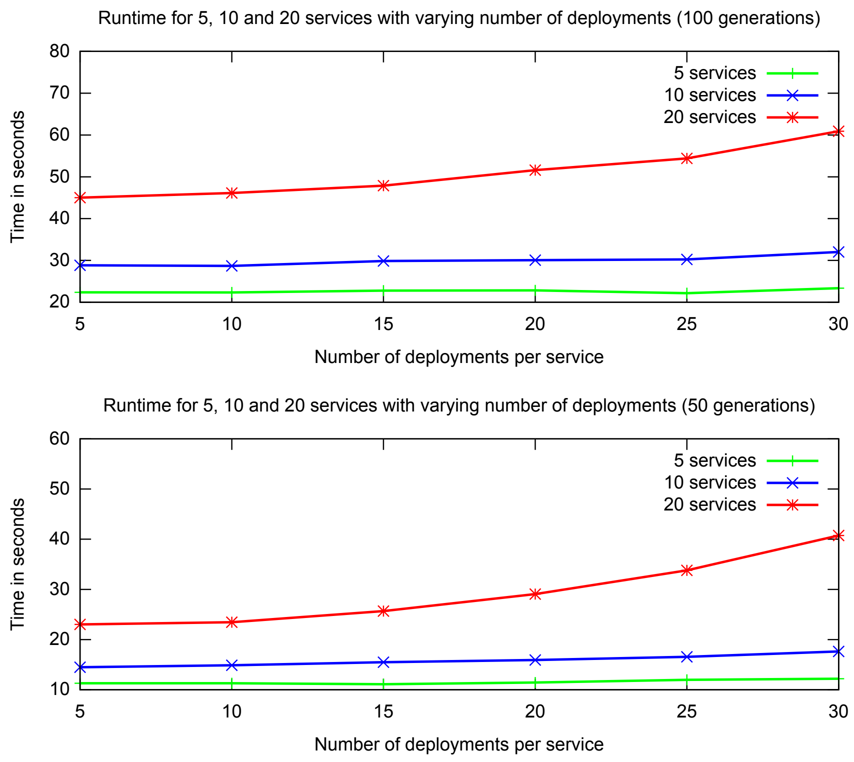


Figure 7.13: Runtime for Increasing System Setups

the logging component. The TASK allows treating the TAG system as a real distributed system, in which different components are hosted at different sites and organizations, under the responsibility of people from different organizations as well.

An independent optimization component can be implemented that allows plugging different concrete optimization algorithms in it. This component will be connected to the data and service catalogs, will get the system status and launch an optimization approach or algorithm. This can be as simple as a rule-based approach (`if request from <site> and requested data in <project>, connect to <deployments>`) or an exhaustive search algorithm, or more complex such as the AD-MOGA approach. Which approach is plugged into the optimization component can depend on the current size of the system, and other parameters.

Figure 7.15 shows the architecture of a possible deployment of the proposed optimization approach in the TAG system. An incoming request is composed of two parts: the request string (e.g., in the form of a list of TAG datasets or TAG collections) and the abstract workflow (e.g., "iELSSI – TAG DB – Extract XML Builder – Extract – Skimming"). The requested data are a direct user input, the abstract workflow is specified based on the use case the user requests (e.g., by clicking on a button that triggers a service execution process). The request is centrally routed to the service selection optimizer (1). The optimizer itself is composed of three components: the *Data Locator*, the *Service Locator* and the *Optimization Component*. When a request is coming in, the requested

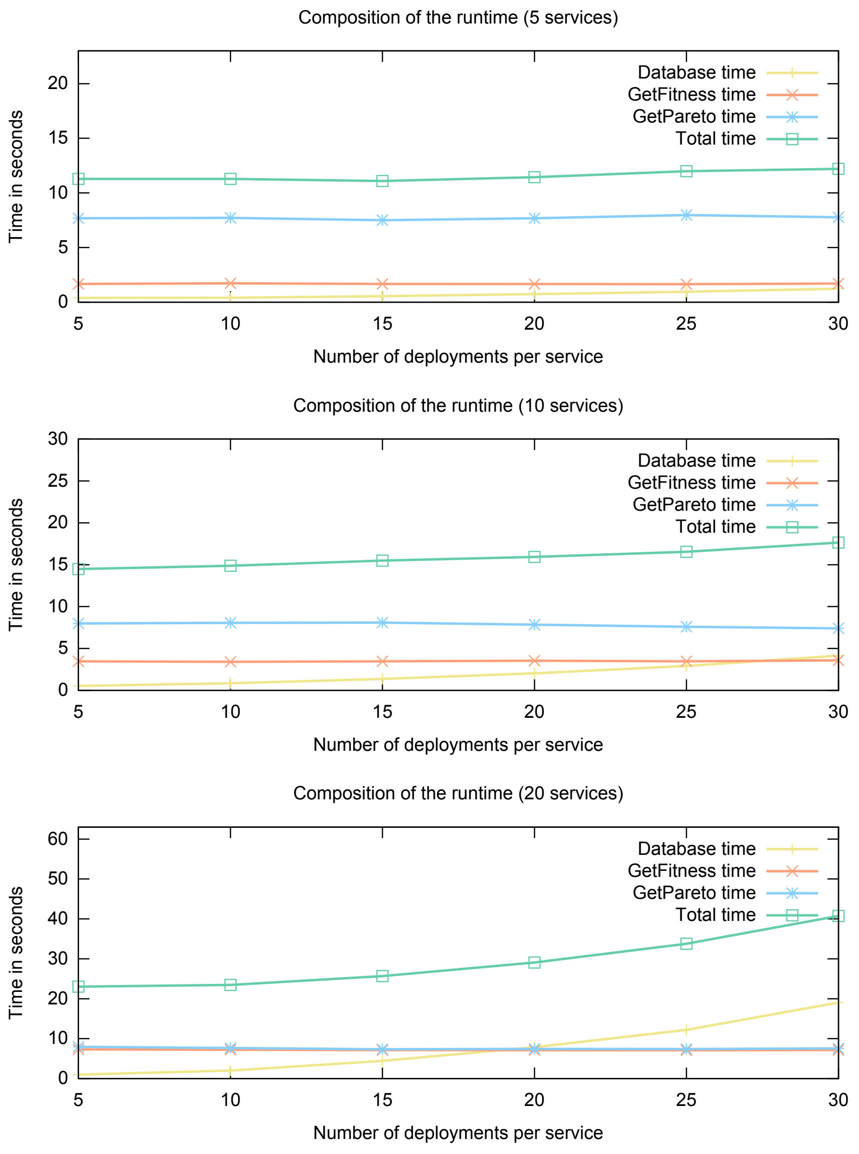


Figure 7.14: Composition of the Runtime

data are sent to the data catalog (2) that returns the list of TAG databases (e.g., in the form of connection strings) that actually contain the data (3), i.e., the set of TAG databases that can be included in the concrete workflow is restricted based on the data availability. The TAG Web services can deal with query splitting and results merging, therefore databases containing a subset of the requested data are also returned, with a list of contained datasets/collections. The list of possible connection strings is handed to the *Service Locator* (4). In step (5), the service locator passes the abstract workflow specification and the connection list to the service catalog, and gets a loaded list or dictionary back, containing all available deployments and their QoS attributes (6). This dictionary, together with the abstract workflow definition, are the input to the optimization component that works as described in detail in Figure 6.5, or, alternatively another optimization approach can be chosen and plugged into this architecture (steps (8) and (9)). Finally, the concrete deployments of the TAG services pool are invoked to compose the concrete workflow (10).

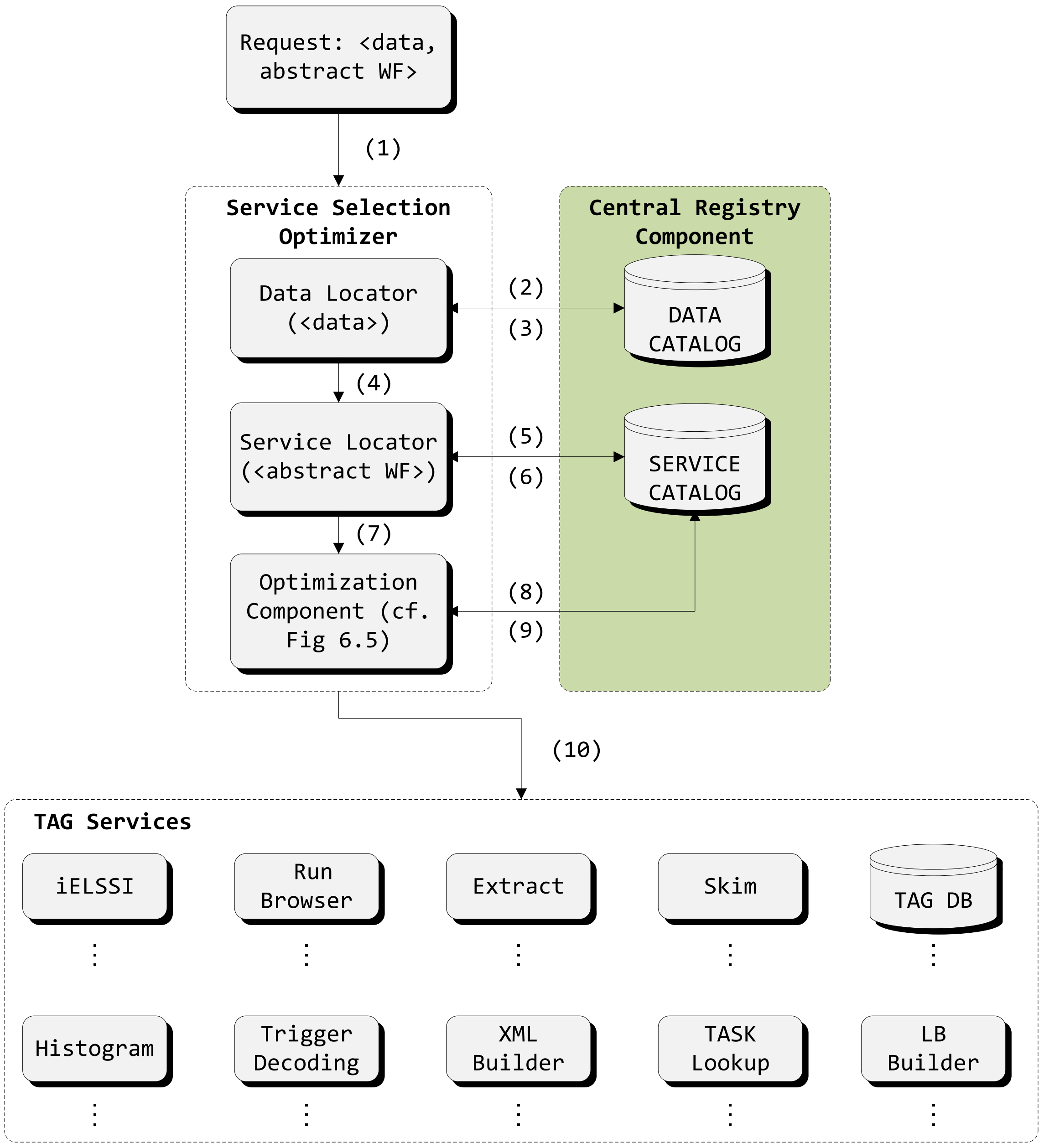


Figure 7.15: Integration of the Optimization Approach into the TAG System

7.6 Practical Considerations for the Implementation

As the research carried out in this thesis has been motivated by and applied to a specific application, it is important to evaluate not only the results, but the entire way of getting to the actual results. In view of applying a similar methodology to other systems, the operational implications are outlined. Figure 7.16 summarizes the design and implementation steps followed throughout this work. The rectangles on the left-hand side depict general steps, those on the right-hand side the specific actions carried out on the TAG system.

When a centralized optimization approach is added to an already existing system, its design has to be adapted to work with the system's components. In the TAG case, the databases and several of the Web services existed, but were not centrally documented and registered, and the data distribution was not documented, making it a federation of independent services and data sources rather than a distributed system. The first step towards a distributed architecture was the design and implementation of the TASK data catalog as described in Section 4.4, hiding the data distribution from the users and other applications. The integration of the logging component and service catalog required contributions from all service developers, because the interface and internals of each service are different. Therefore, a common API has been defined, but adaptations were made for each service. As changes in the service's implementations might have an impact on their logging component, for instance, these dependencies have to be considered and kept up to date. Such operational efforts come however with positive "side-effects," i.e., advantages that have not originally been planned for. Examples are listed in the following:

- The registry acts as a "dynamic" (or "self-adaptive") documentation of the system.
- The data in the registry allows having detailed knowledge about the status of any system component at any time. The tracking of changes allows documenting the evolution of the system components. This further allows noticing trends, for example the degradation of a usage or performance index that might indicate intrinsic errors.
- The logging information can be further used to mine data about the system usage.
- The central registry (in the TAG case the TASK Service Catalog) can be used as a repository for service configurations, therefore allowing an automated configuration management (on a basic level, not to be confounded with dedicated configuration management tools).

Based on the experience of implementing and operating a knowledge base and service discovery mechanism in the TAG system, the following recommendations can be made:

- If possible, it is evidently beneficial to include service discovery and selection in the initial system design.
- In a distributed system involving developers from different organizations and locations, it is important to have a strong commitment for a centralized service selection approach.
- If a rather small system is deployed, but it is expected to grow in terms of number of services and deployments, a flexible optimization framework allowing plugging in different service

selection algorithms is desirable. This way, depending on the size of the system, different algorithms can be run.

- The operations of the registry and other components related to the service selection should be part of the general system's operations.

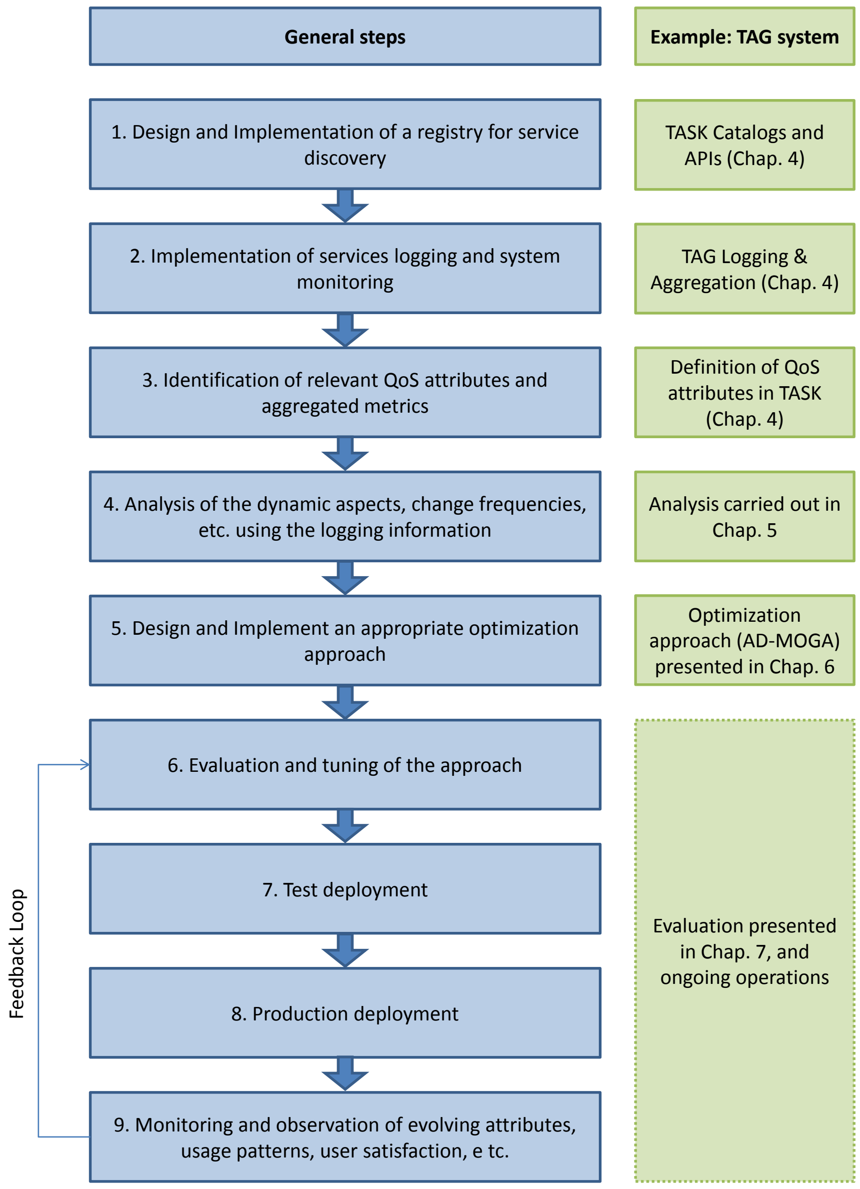

General steps
Example: TAG system
1. Design and Implementation of a registry for service discovery
TASK Catalogs and APIs (Chap. 4)
2. Implementation of services logging and system monitoring
TAG Logging & Aggregation (Chap. 4)
3. Identification of relevant QoS attributes and aggregated metrics
Definition of QoS attributes in TASK (Chap. 4)
4. Analysis of the dynamic aspects, change frequencies, etc. using the logging information
Analysis carried out in Chap. 5
5. Design and Implement an appropriate optimization approach
Optimization approach (AD-MOGA) presented in Chap. 6
6. Evaluation and tuning of the approach
7. Test deployment
8. Production deployment
9. Monitoring and observation of evolving attributes, usage patterns, user satisfaction, e tc.
Evaluation presented in Chap. 7, and ongoing operations
Feedback Loop

Figure 7.16: Outline of Design and Implementation Steps

7.7 Possible Extensions in Future Work

The presented optimization framework is self-contained and can be deployed as it is. However, there are several areas of possible enhancements and extensions that make the overall approach more fine grained, robust, and allow for a wider scope. The identified areas are schematically represented in Figure 7.17 and described in the following:

Algorithmic Approaches. In the proposed approach, a GA is at the heart of the optimization. It has been shown that it is particularly suited for dynamic service selection problems. However, its usefulness depends on the size of the problem. For very small problems, e.g., with five services having two deployments each, an exhaustive search algorithm is a better option and, as opposed to a heuristic, guarantees returning the optimal solution. Additionally, the approaches presented in Chapter 3, Section 3.4, can be prototyped and included as possible available optimization algorithms. Then, depending on the problem size and characteristics, one of the algorithms can be chosen to optimize the service selection.

QoS Models. In the considered system, performance and usage indexes are considered as the primary variables that decisions are based on. It could however be useful to carry out simulations with different aggregated QoS metrics and compare the results, especially in terms of system throughput. The choice of the "right" QoS metrics to take into account is not trivial and can be based on simulation results indicating the resulting system behavior. Therefore, in the same way as different algorithms can be implemented and compared, different QoS models can be included in the framework.

Fine-grained Weighting. Weights assigned to QoS attributes are another area of possible extensions. Weights can be assigned at different levels in order to refine the preferences during the deployment selection process. In this work, weights are defined on optimization objectives through optimization profiles. However, in many systems the assignment can be a more complex process. Weights on attributes can be defined based on the involved abstract services and the nature of the concrete request. For example, if the invocation of service `B` from service `A` requires data transfer, and a given request is defined on a large amount of data, then the throughput of the link between service `A` and service `B` is more important (has a higher impact) than its latency. Therefore, mechanisms determining those kinds of weights on the fly, based on pre-defined attributes and on the analysis of logging information and/or simulation results, can be designed and implemented.

Model Simulation. Finally, it is important to verify the above-mentioned extensions and model options through simulation. The system can either be represented in a custom database model, as in the evaluation carried out in this thesis, or simulation tools such as SimGrid [23] can be customized and used to build a system model and run specific simulations on it. The ultimate goal is not only to be able to compare algorithms and QoS models, but also to allow for system capacity planning. For instance, in terms of planning it is crucial to determine the consequences of adding or removing deployments (with specific QoS categories). If the overall performance of a distributed system is degrading due to a high utilization resulting in a high load on the underlying resources, the issue can be addressed either by optimizing the current system setup, or by adding new resources. In a distributed system, it is crucial *where* to add a deployment. This question can be addressed by adding a virtual resource to the model and performing simulation runs of typical workload. This allows building the capacity planning process on robust decisions.

Aggregating the above-described parts allows building an Anytime Learning System for addressing QoS-aware service selection problems under different and changing conditions. Anytime learning refers to a generic approach to continuous learning in a system that changes and evolves over time [73]. Figure 7.18, derived from the architecture proposed by Ramsey and Grefenstette in [73], shows a possible anytime learning architecture in this context. It is composed of two main parts, the *execution* system and the *learning* system. In the execution system, a decision maker interacts with the monitored distributed system and optimizes deployment selections by not only accessing the service registry containing the QoS metrics, but also an active knowledge base that stores information about good optimization approaches. This knowledge base can be seen as an extended version of the persistent memory introduced in Chapter 6. It contains strategies to be applied to the optimization, depending on the system environment, the nature and frequency of changes, etc. In the learning system, new strategies (e.g., algorithms, QoS models) are applied and their impact is evaluated. If a strategy proves to be better than the ones in the execution system, it is transferred from the test knowledge base to the active knowledge base. The ultimate goals of applying such an anytime learning system include:

- Decide on the most appropriate algorithmic approach to be applied for deployment selection.
- Decide on QoS models that best reflect the real system.
- Track environmental changes over the system lifetime and derive profiles regarding usage, optimization, utilization, etc.
- Test and assess changes in the system configuration.

In addition to the above mentioned areas, it is interesting to explore different ways of computing the similarity index (cf. Chapter 5, Section 5.2.3). The index computation introduced in this thesis with the goal of providing a quantification of system changes between time t and time $t+\Delta t$ is a first attempt, but other approaches can be investigated. The presented index has a few shortcomings. For example, if a concrete workflow composed of four deployments is considered, each deployment belonging to a service containing 20 different deployments each, and one deployment per service changes between t and $t+\Delta t$, the resulting similarity index is high (only 4 changed deployments out of 80). However, if by coincidence exactly those four deployments making up the previously computed optimal solution are affected by the changes, then the real impact can be higher than expressed by the similarity index. It is thus worthwhile to consider such special cases and embed the similarity computation into a broader framework.

7.8 Summary

The findings of the evaluation of AD-MOGA can be summarized as follows:

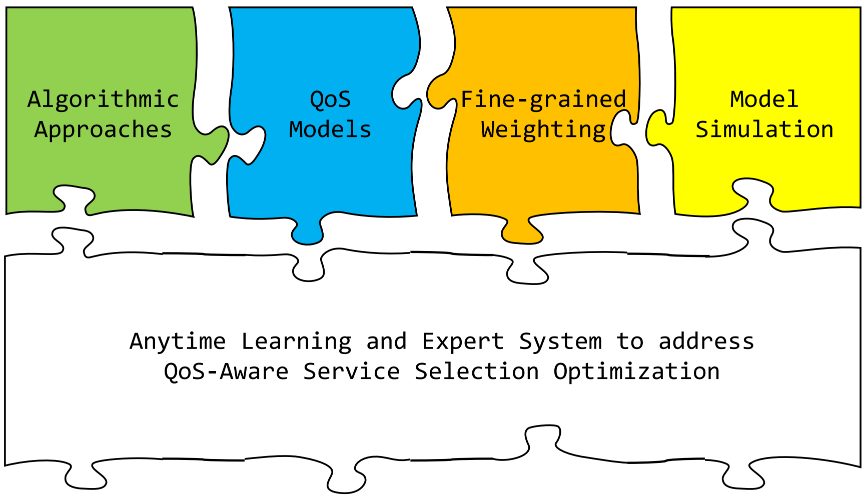

Algorithmic Approaches
QoS Models
Fine-grained Weighting
Model Simulation
Anytime Learning and Expert System to address QoS-Aware Service Selection Optimization

Figure 7.17: Areas for Future Extensions

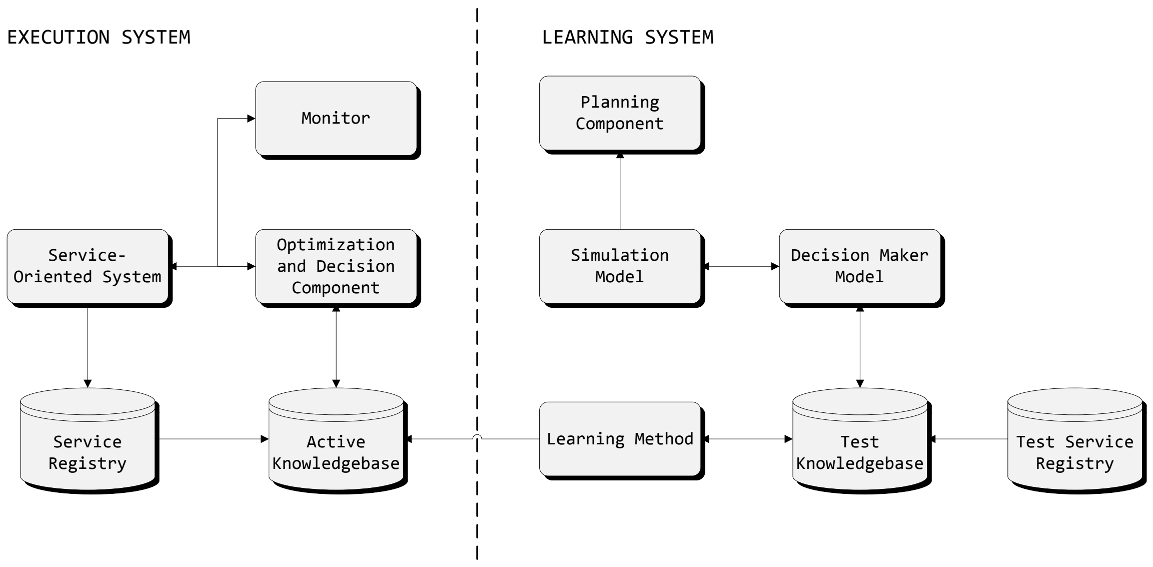


Figure 7.18: Anytime Learning System for Service Selection Optimization

- For a set of studied input parameters, AD-MOGA converges towards the Pareto front in a range of 60 to 100 generations for realistic problem sizes.

- AD-MOGA adapts to changes in the environment by identifying system changes and their impact, and adapting its initialization and its mutation rate accordingly. This results in a quicker convergence towards the Pareto front, if information from past computation can be reused. If the system changes radically (similarity index below 0.5), a restart of the optimization with a random initialization is however preferable.

- Experiments have shown that the more changes there are, the higher the mutation rate should be, in order to ensure a high diversity in the population. This is valid up to a change rate of about 50%, above which a complete random restart is the better option.
- In terms of runtime, AD-MOGA scales well to big but realistic problem sizes. The most cost-intensive phases in the algorithm are the computation of the overall workflow fitness (performance and usage) and the identification of the Pareto candidates in each generation. Therefore, these are areas to focus on for future improvements. Specifically, external mathematics packages taking for instance advantage of vectorization techniques can be used to determine the Pareto candidates.

Those findings are represented in Figure 7.19 in the form of a structured decision tree. The left-most leaf, called root leaf, is the starting point. The first decision concerns the problem space. The evaluation showed that for a system setup with 5 services having 20 deployments each, and a workflow of 5 services, the exhaustive search algorithm is not an option anymore, because its runtime is of the order of minutes. However, the exact definitions of "big" and "small" have to be evaluated on a per-scenario basis, which is why those qualitative expressions are kept in the decision tree. For "big" problem setups, AD-MOGA is used, and the further options – such as random (re)start, (re)start from memory and adaptation of the mutation rate – depend on the impact of changes occurring between and during optimization runs.

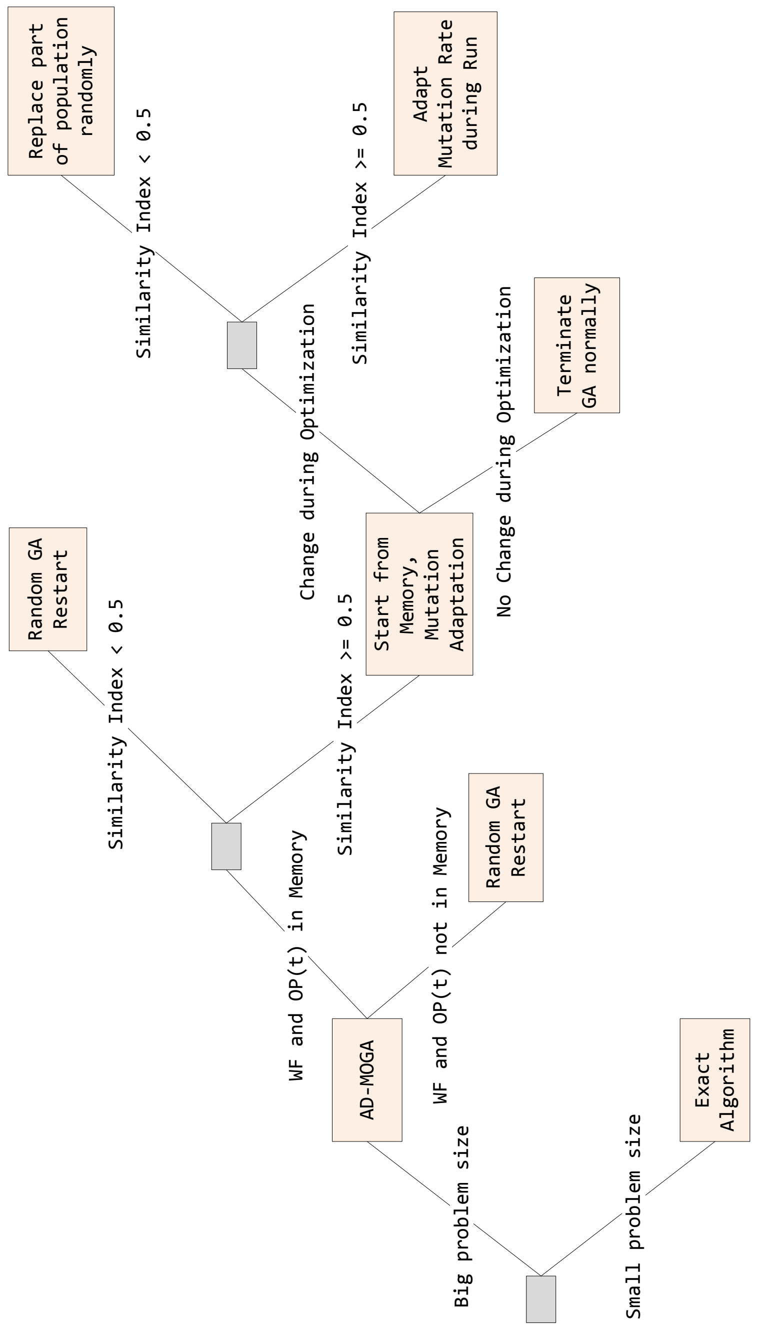


Figure 7.19: Decision Tree Summarizing the Evaluation Findings

Chapter 8

Conclusion

Quality-aware service selection is about choosing concrete services (deployments) for a workflow in such a way that Quality of Service (QoS) considerations are optimized. This broad topic has become crucially important with the emergence of large, service-oriented systems, in which an abstract service usually exists in several, distributed concrete deployments. When instantiating a workflow, deployments have to be selected and composed at run-time. This thesis work has been motivated by the service selection challenge arising in a concrete application, the TAG system in the ATLAS experiment. The TAG system is characterized by a central control instance, tightly coupled services, a dynamic environment, and changing objectives and priorities. This thesis investigates specific aspects of the QoS-aware service selection problem and makes three contributions to the research area:

1. A high-level ontology for describing the components and QoS attributes of service-oriented systems is proposed. This ontology specifies a vocabulary for describing the elements required to formulate a service selection optimization problem on a specific system. It is shared between providers of distributed services and aims at providing a shared understanding of a system. As opposed to detailed and complete system models, the proposed ontology focuses specifically on the elements required for the service selection process.

2. QoS-aware service selection is defined as a dynamic, multi-objective optimization problem. Multiple objectives for such problems are common in related work, but the dynamic aspects have been neglected in related problem definitions. Starting from the analysis of the dynamics in the studied TAG application, system and optimization profiles are introduced. These profiles define the state of the system and the optimization instance at a given point in time. The optimization itself is carried out from two conflicting perspectives, namely the user's and the provider's perspective. The resulting problem is modeled as a multi-objective, multi-constrained optimal path problem.

3. A dynamic and adaptive multi-objective genetic algorithm is designed, implemented and evaluated. It is tailored to address dynamic QoS-aware service selection problems and efficiently analyzes the changes in the underlying system to reduce its runtime. Evaluation results demonstrate the applicability and accuracy of the approach as well as its scalability to systems with

a large number of components and services.

In future work, the optimization framework can be extended towards other algorithmic approaches, in order to provide a testbed for different algorithms on dynamic service selection problems. Furthermore, an Anytime Learning System addressing the specific challenges of dynamic service selection identified in this thesis can be derived. The learning component of such a system can then both vary adaptation methods of a genetic algorithm, for instance AD-MOGA, and try different algorithms (defined in the extended optimization framework) to update the knowledge base used by the decision maker on the execution environment. The simulated environment used in the evaluation part of this work can serve as a learning system, while the TAG application is a real-world execution system. The work presented in this thesis is an enabling step in that direction.

For concluding the thesis, I have been asked to formulate seven statements related to the thesis, and three general statements, as personal reflections:

1. Scientific applications involving data-intensive services are particularly appropriate scenarios for studying QoS-aware service selection problems.
2. It is more accurate to model the service selection as a constrained optimal path problem than as a knapsack problem, because neglecting the QoS of links between services considerably biases the overall workflow QoS.
3. Metaheuristic algorithms are the most promising approaches to real-world service selection problems, because they scale well to typical problem sizes arising in the World Wide Web.
4. Components of service-oriented systems and their QoS attributes can be precisely defined via ontologies for a given domain of discourse.
5. The QoS-aware service selection challenge can be formulated as a *dynamic* multi-objective optimization problem.
6. A persistent memory and a change tracking system provide an efficient means to leverage the usage of genetic algorithms to solve dynamic service selection problems.
7. The implementation of a QoS registry and a service selection optimization framework in a real-world system considerably augments the manageability of the system.
8. Pragmatism is an important attitude while finishing a PhD thesis, and probably any other mid- and long-term project.
9. The importance given to a thing is a function of the viewpoint and experience one has on the thing.
10. There is no such thing like music to express the whole spectrum of nuances and colors of reality and imagination.

Appendix A

System and Attribute Ontology: OWL Schemas

A.1 OWL Definitions Used in the Ontologies

OWL is a Web Ontology language developed by the World Wide Web Consortium (W3C). It is a language for knowledge representation based on the Resource Description Framework (RDF), which is another W3C standard for data exchange on the Web [99]. It is used for describing information conceptually, and thus acts as a metadata model for a given domain of interest. In the following, the OWL concepts and constructs used in the system and attribute ontology are shortly described. The definitions are based on those provided in [48] and [98].

Individual. Individuals are objects from the domain described by the ontology, also referred to as the *domain of discourse*. In the example at hand, a service oriented computing system is the domain of discourse, and objects are instances of servers, services, etc. OWL does not use the Unique Name Assumption, therefore two individuals must be explicitly defined as being the same or distinct from each other.

Class. A class is a group of individuals sharing some properties. Classes are organized hierarchically in a superclass-subclass manner. Subclasses inherit properties from their subclass(es). All classes are subclasses of the root class `Thing`. If classes are *disjoint*, then an individual can only belong to exactly one of these classes. *Defined* classes have a precise definition, i.e., *necessary* and *sufficient* conditions, and any individual that satisfies those conditions belongs per definition to the class. Classes without such a definition are referred to as *primitive* classes – they only have *necessary* conditions.

Property. Properties are used to model relationships between individuals (*object properties*) or between individuals and data types (*data properties*). Properties can have specified *domains* and *ranges*, i.e., they relate individuals from the domain (class) to individuals from the range (class). For example, the property `hosts` links individuals from the class `Provider` to individuals from the class `Resource`. The property `isHostedBy` is the *inverse property* of `hosts` and domain and range are flipped over. If a property is *functional*, then every individual can be linked to only exactly one other individual via this property. If a property is *transitive*, then if it relates individual `A` to individual `B` and `B` to `C`, it can be concluded that it also relates `A` to `C`. If a property that relates `A` to `B` necessarily implies that this same property also relates `B` to `A`, then the property is called *symmetric*. If in turn the fact that a property relates `A` to `B` implies that the same property cannot relate `B` to `A`, it is called *asymmetric*. A property is called *reflexive* if it must relate an individual to itself, and *irreflexive* it if cannot relate an individual to itself.

Restrictions. A restriction describes a class of individuals based on the relationships that members of these classes have with other individuals. There are three restriction categories: *Quantifier Restrictions*, *Cardinality Restrictions* and *hasValue Restrictions*. Quantifier restrictions can be *existential* or *universal*. Existential restrictions describe classes of individuals that have *at least one* relationship via a specific property to individuals of a specific class (keyword `some` in Protégé). Universal restrictions describe classes of individuals that are linked to other individuals through a given property to *only* individuals from a specific class (keyword `only` in Protégé). Cardinality restrictions define the number of relationships an individual has for a given property (minimum, maximum, exact number). A hasValue restriction defines a class of individuals that are related to a *specific* individual with a certain property. Finally, a *Closure Axiom* on a property is a universal restriction for this property that restricts the possible ranges of the property.

A.2 System Ontology: OWL Schema

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    <!ENTITY rdfs "http://www.w3.org/2000/01/rdf-schema#" >
    <!ENTITY rdf "http://www.w3.org/1999/02/22-rdf-syntax-ns#" >
]>
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     xmlns:rdfs="http://www.w3.org/2000/01/rdf-schema#"
     xmlns:xsd="http://www.w3.org/2001/XMLSchema#"
     xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#"
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    <AnnotationProperty abbreviatedIRI="rdfs:comment"/>
    <IRI>#System</IRI>
    <Literal datatypeIRI="&rdf;PlainLiteral">A Computing System composed of several
        components that can act together to provide some defined functionality to
        users interacting with the system, be it humans or other systems.</Literal>
</AnnotationAssertion>
<AnnotationAssertion>
    <AnnotationProperty abbreviatedIRI="rdfs:comment"/>
    <IRI>#SystemComponent</IRI>
    <Literal datatypeIRI="&rdf;PlainLiteral">Logical or physical building block of a
        system.</Literal>
</AnnotationAssertion>
<AnnotationAssertion>
    <AnnotationProperty abbreviatedIRI="rdfs:comment"/>
    <IRI>#hasID</IRI>
```

```
        <Literal datatypeIRI="&rdf;PlainLiteral">Each instance of a SystemComponent has
            exactly one unique identifier.</Literal>
    </AnnotationAssertion>
    <AnnotationAssertion>
        <AnnotationProperty abbreviatedIRI="rdfs:comment"/>
        <IRI>#hasName</IRI>
        <Literal datatypeIRI="&rdf;PlainLiteral">Each individual in the ontology has to
            have exactly one name.</Literal>
    </AnnotationAssertion>
    <AnnotationAssertion>
        <AnnotationProperty abbreviatedIRI="rdfs:comment"/>
        <IRI>#isAtomic</IRI>
        <Literal datatypeIRI="&rdf;PlainLiteral">defines if a SystemComponent is atomic
            or composed.</Literal>
    </AnnotationAssertion>
    <DatatypeDefinition>
        <Datatype abbreviatedIRI="xsd:boolean"/>
        <Datatype abbreviatedIRI="xsd:boolean"/>
    </DatatypeDefinition>
</Ontology>

<!-- Generated by the OWL API (version 3.2.3.1799) http://owlapi.sourceforge.net -->
```

Glossary

ACO Ant Colony Optimization. 44

AD-MOGA Adaptive and Dynamic Multi-Objective Genetic Algorithm. 7

AMI tag Refers to a version tag that is part of a dataset name and allows tracking the software version and configuration used to produce the dataset. For example, in the dataset `data11_7TeV.00184169.physics_MinBias.merge.TAG.f387_m897_m896`, the last part namely, the string `f387_m897_m896`, is the AMI tag. Not to be confounded with the data product TAG and the TAG system studied in the context of this work. 71

ANN Artificial Neural Network. 45

AOD Analysis Object Data. Refers to a reduced event representation (output of the data reconstruction process), derived from ESD, suitable for most physics analyses. 15

ATLAS A Torroidal LHC Apparatus. One of the four large "experiments" (detectors) at the Large Hadron Collider. 1

BB Branch-and-Bound. 39

CERN Organisation Européenne pour la Recherche Nucléaire (European Organization for Nuclear Research). 4

Collection Is a structure developed by ATLAS as part of the POOL framework. POOL collections are data structures for event data that can be stored in both ROOT and relational formats. 16

DAG Directed Acyclic Graph. 38

dataset Refers to a set of data grouped together. The most common grouping is based on physics stream, run and data type.
For example, `data11_7TeV.00184169.physics_MinBias.merge.TAG.f387_m897_m896` is the name of a dataset grouping TAG data (events) from the MinBias stream in run 184169. 71

EA Evolutionary Algorithm. 43

ESD Event Summary Data. Refers to event data written as first output of the data reconstruction process, taking RAW data as input. 15

Event In particle physics, an event refers to a collision instance and its set of particle interactions and intermediate as well as stable products. 13

Event Filter Last element of the ATLAS trigger system. As such, it is the source of real data from the ATLAS detector. 15

GA Genetic Algorithm. 9

GLG Geometric Location Guided. 41

GUID Globally Unique Identifier, refers to a unique identifier of a file on the Grid. GUIDs can be dereferenced to physical file locations using a metadata catalog lookup. 17

HEP High Energy Physics. 1

iELSSI interactive Event Level Selection Service Interface. iELSSI is a TAG service that allows browsing the TAG databases on the Web. 20

LHC Large Hadron Collider. 1

LP Linear Programming. 38

LRA Local Resource Amplest. 41

Lumiblock Time interval (in practice one to two minutes) during which luminosity and detector conditions can be assumed stable. It is used as granularity in data taking and processing. 20

MCOP Multiconstraint Optimal Path Problem. 3

MIP Mixed Integer Programming. 37

MMKP Multi-dimension Multi-choice Knapsack Problem. 2

MOGA Multi-Objective Genetic Algorithm. 106

MOOP Multi-Objective Optimization Problem. 47

NSGA-II Nondominated Sorting Genetic Algorithm II. 125

OWL Web Ontology Language. 53

POOL Pool Of persistent Objects for LHC. POOL is a hybrid technology store for C++ objects, using a mixture of streaming and relational technologies to implement both object persistency and object metadata catalogs and collections. It provides generic components that allow isolating applications from the storage technology used [82]. 16

PSO Particle Swarm Optimization. 44

QEP Query Execution Plan. 29

QoS Quality of Service. 2

RAW Collision data (in byte stream format) as it is written as output from the particle detector, here ATLAS. 13

RDF Resource Description Framework. 161

Reprocessing Refers to the process of reconstructing previously taken RAW data with improved reconstruction software and calibration constants. This results in a new version of data, called reprocessed data. 17

ROOT Is a framework for data processing developed at CERN. It allows processing, accessing and saving data and any C++ object in a compressed binary form, and to show results in histograms, scatter plots, etc. ROOT provides a data structure that is extremely powerful for fast access of huge amounts of data [5]. 15

Run Period of data taking, usually defined by the duration of an LHC fill. A run is thus also a means of grouping data. 17

SAW Simple Additive Weighting. 38

SOA Service Oriented Architecture. 28

SOAP Simple Object Access Protocol. 28

SPEA2 Strength Pareto Evolutionary Algorithm 2. 124

TASK TAG Application Service Knowledge base. 20

Tier Refers to a Tier of ATLAS, designating a site (as big as a main computing center, or as small as a local institute cluster) taking part in the LHC Computing Grid and providing computing and storage resources to the ATLAS experiment. 4, 54

Tier-0 Refers to CERN as the central data taking tier of ATLAS and the root tier in the Grid hierarchy. Its main responsibilities are the archiving of data, first-pass processing (reconstruction), and the distribution of RAW and derived data to other tiers of ATLAS. 14

Tier-0 Management System Refers to the software for managing, orchestrating, executing and monitoring the Tier-0 internal data and workflows for ATLAS [38]. In particular, the Tier-0 management system uploads file-based TAGs to the TAG databases. 15

Trigger Refers to a multi-level system that filters events recorded by the detector, letting only a given fraction of events pass. Thus, it allows reducing the recorded data to a set of "interesting" events, according to the trigger criteria. 15

W3C World Wide Web Consortium. 28

WLCG Worldwide LHC Computing Grid. Its aim is to provide a distributed computing infrastructure for the storage and processing needs of the LHC experiments. ATLAS sites are a subset of WLCG sites. 14

WSDL Web Service Definition Language. 28

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Curriculum Vitae

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Date of Birth	March 16th, 1983
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Education

Since 11/2008	Doctoral Student in Computer Science at the University of Vienna and CERN. Thesis in the area of QoS-aware Service Selection Problems. Database and software development for the ATLAS TAG project.
03/2006	Master degree in Business Informatics from the University of Vienna.
09/2004 - 12/2004	Research stay at the Ecole Nationale Supérieure des Mines de Saint-Etienne, France. Leonardo da Vinci scholarship for student placement.
2002 - 2006	Studies of Business Informatics, University of Vienna.
2001 - 2002	Studies of Molecular Biology, University of Vienna.
1989 - 2001	Lycée Français de Vienne, Baccalauréat général, Série Scientifique (2001).

Work Experience

06/2005 - 10/2008	Vienna University Computer Center: software development (data warehousing), computing operations, project coordination and user support.
07/2002	Internship at BOC Ltd., Dublin, Ireland.

Informatics Skills

Programming	Python, PHP, Java
Databases	Oracle 10g and 11g, PL/SQL, Data Warehousing, Reporting Tools

Language Skills

German	native
English	excellent
French	excellent
Italian	conversant

Publications

- E. Vinek, P.P. Beran and E. Schikuta. Comparative Study of Genetic and Blackboard Algorithms for Solving QoS-Aware Service Selection Problems. Accepted as poster at *The 2011 International Conference on High Performance Computing & Simulation (HPCS 2011)*, Istanbul, Turkey, 2011.

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