# A Distributed Approach to QoS-aware Cloud Resource Scheduling 

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an der Fakultät für Informatik
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Betreuung: Assistant Prof. Dr.-Ing. Stefan Schulte

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# A Distributed Approach to QoS-aware Cloud Resource Scheduling 

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## Alexander Prennsberger, B.Sc.

Registration Number 1129308
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Advisor: Assistant Prof. Dr.-Ing. Stefan Schulte

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## Alexander Prennsberger, B.Sc.

Petrigasse 5/4/6
2604 Theresienfeld

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## Kurzfassung


#### Abstract

Cloud Computing ist eine der wichtigsten Technologien um on-demand Services über das Internet verfügbar zu machen. Cloud Computing basiert auf der sogenannten Virtualization Technologie, über welche Cloud Konsumenten Zugriff auf theoretisch "unendlich" viel Rechenleistung haben. Diese wird üblicherweise über ein nutzungsbasiertes Preismodell angeboten. Das Ressourcen Scheduling Problem in der Cloud ist NP-Schwer. Es bezeichnet die Zuordnung von Workloads der Cloud Benutzer zu verfügbaren Ressourcen. Ziel der Cloud Anbieter ist es, hohe QoS (Kosten, Verfügbarkeit, Einhaltung von Deadlines) Standards einzuhalten. Cloud Konsumenten können jedoch überall auf der Welt verteilt sein und es ist zum Beispiel ineffizient Workloads von Konsumenten aus Europa in asiatischen Datenzentren zu bearbeiten. Durch die große geographische Distanz kann es außerdem der Fall sein, dass manche QoS Standards nicht mehr eingehalten werden können weil z.B. die Antwortzeiten zu groß sind. Deshalb sollten Ressourcen von verschiedenen Datenzentren an verschiedenden Standorten beim bearbeiten von Workloads berücksichtigt werden. Um das zu ermöglichen benötigt es verteilte Prozesse.


In dieser Arbeit wird ein verteilter Ansatz für Ressourcen Scheduling in der Cloud - unter Berücksichtigung von QoS Standards - vorgestellt. Der Ansatz ist in zwei Phasen gegliedert: (i) Lokale Scheduling Phase und (ii) Resource Discovery Phase. In der Scheduling Phase werden Workloads auf verfügbaren Ressourcen zugeordnet. Dieses Optimierungsproblem wird mit Hilfe einer Particle Swarm Optimization Heuristik gelöst. Das lokale Scheduling findet innerhalb eines Datenzentrums statt. In der Resource Discocery Phase werden Workloads an andere Datenzentren weitergeleitet. Diese prüfen ob sie genug verfügbare Ressourcen haben um den Workload abarbeiten zu können. Wenn ja, antworten sie dem Sender mit Informationen zu ihren Ressourcen. Dadurch ist es möglich, lokale Ressourcen innerhalb eines Datenzentrums durch externe Ressourcen zu erweitern. Diese werden dann in der Scheduling Phase berücksichtigt.

Mit Hilfe des CloudSim Frameworks wurde eine Simulation des Ansatzes durchgeführt. Die erzielten Ergebnisse zeigen, dass die Ausführungskosten von Workloads im Vergleich zu einem zentralen Scheduling Ansatz deutlich geringer sind. Die Einhaltung von Deadlines und Budgets ist ebenfalls besser wenn ein verteilter Ansatz verwendet wird. Vor allem bei sehr knappen Deadlines und in Szenarien mit sehr vielen Workloads sind die größten Verbesserungen durch einen verteilten Ansatz zu erkennen.

## Abstract

Cloud computing is one of the most important technologies for delivering on-demand services over the internet and has grown very fast over the last few years. Based on the virtualization technology, cloud consumer have access to seemingly "unlimited" computing power in a pay-as-you-go manner. The cloud resource scheduling problem, where tasks from cloud users are mapped to cloud resources is known to be NP-hard. The aim of each cloud provider is to deliver high QoS (cost, availability, deadlines) to their users. Because cloud users could be from anywhere in the world, it would be inefficient to schedule for example resources in Asian data centers to European users. Also the QoS requirement of meeting application deadlines could not be met if response times are high. Hence, cloud resources from different locations (e.g. data centers) must be utilized to fulfill adequate response times for geographically-dispersed cloud consumers. In order to tackle these challenges, scheduling approaches should consider distributed cloud resources among different data centers using distributed processes.

This work proposes a distributed approach to QoS-aware cloud resource scheduling. The overall approach is divided into two phases: (i) local scheduling phase and (ii) resource discovery phase. In the scheduling phase workloads are mapped to available resources using a Particle Swarm Optimization heuristic. This is done within a single data center. In the resource discovery phase, an incoming task (workload) is forwarded to adjacent data centers in order to determine if the have available resources which can handle the workload. If they are capable of processing the workload they send back a message to the requesting data center with their resource information. In this way, the local available resources within a single data center can be extended by remote resources from other data centers. They are then considered during the scheduling phase and are treated as local resources.

An experimental simulation of the approach was conducted in the CloudSim framework. The observed results showed that the execution cost of submitted task are significantly lower for the distributed scheduling approach compared to a centralized one where only a single data center exists. Also the deadline violation rates and task completion rates are better when using the distributed approach. This is especially the case for very tight deadlines and large scale environments with many tasks. Because the distributed approach can utilize more resources from other data centers the results are better.

## Contents

Kurzfassung ..... vii
Abstract ..... ix
1 Introduction ..... 1
1.1 Motivation and Problem Statement ..... 1
1.2 Aim of the Work ..... 2
1.3 Methodological approach ..... 3
1.4 Structure of the Work ..... 4
2 State of the Art ..... 5
2.1 QoS-aware Cloud Computing ..... 6
2.1.1 Quality of Service and Service Level Agreements ..... 6
2.1.2 Cloud architecture ..... 7
2.1.3 Autonomic Resource Scheduling ..... 8
2.2 Optimization in the Cloud ..... 10
2.2.1 Cloud Resource Scheduling Problem ..... 10
2.2.2 Optimization Methods ..... 12
2.2.3 Evolutionary Computation (EC) ..... 14
2.2.4 Optimization Architecture ..... 19
2.3 Analysis of existing approaches ..... 20
2.4 Research Questions ..... 27
3 Optimization Scheduling Approach ..... 29
3.1 Problem Definition and System Model ..... 29
3.1.1 Motivating Scenario ..... 29
3.1.2 Definition of Tasks and Resources ..... 31
3.1.3 The System Model ..... 33
3.1.4 Geographic Extension ..... 35
3.2 Local Optimization ..... 35
3.2.1 QoS-aware Optimization Model ..... 36
3.2.2 Local Resource Scheduling ..... 37
3.3 Distributed Scheduling ..... 42
3.3.1 Resource Discovery Approach ..... 44
3.3.2 Estimation of Processing Cost and Time ..... 48
3.3.3 Treating Remote Data Centers as Local Resources ..... 49
3.3.4 Resource Manager ..... 49
4 Implementation ..... 51
4.1 CloudSim 4.0 ..... 52
4.2 Local Resource Scheduling ..... 53
4.3 Global Resource Discovery ..... 55
5 Evaluation ..... 57
5.1 Experimental Setup ..... 57
5.2 Simulation Scenarios ..... 58
5.3 Results and Comparison ..... 60
5.3.1 Statistical Analysis ..... 60
5.3.2 Evaluation of Execution Cost ..... 62
5.3.3 Evaluation of Deadline Violation ..... 62
5.3.4 Evaluation of Task Completion ..... 66
5.3.5 Evaluation of Makespan ..... 66
5.4 Summary of the Observed Results ..... 71
5.5 Limitations and Future Work ..... 73
6 Conclusion ..... 75
List of Figures ..... 77
List of Tables ..... 78
List of Algorithms ..... 79
Bibliography ..... 81
Appendix A ..... 87

## Introduction

### 1.1 Motivation and Problem Statement

Cloud computing has emerged in the last years as one of the most important technologies for delivering on-demand services over the internet [1]. These subscription-based services are provided in a pay-as-you-go manner to customers [2]. Cloud computing facilitates a new way of how "users access services based on their requirements without regard to where the services are hosted or how they are delivered" 3. Based on the virtualization technology [4], cloud providers are able to offer seemingly "unlimited" virtual resources and can easily scale these resources (acquire and release) if customer demands are changing. The great flexibility offered by cloud computing and the fact that consumers only pay for used resources makes cloud computing attractive for commercialization [5]. Cloud providers build their data centers at different geographically locations to be available for a worldwide set of internet users [6].

However, with great flexibility also comes complexity and challenges arise when providing dynamic cloud resources. One challenge is that virtualization requires some kind of resource scheduling to efficiently map incoming workloads to available virtual resources. Such resource scheduling problems are known to be NP-hard [7]. Another challenge arises from cloud provider's aim to deliver high quality of service (QoS) in context of reliability, response time and cost to cloud consumers [6]. It is highly unlikely that a single cloud provider owns data centers in all geographic regions of the world to meet the low-latency access required in QoS agreements [8]. Because cloud users could be from anywhere in the world, it would be inefficient to schedule for example resources in Asian data centers to European users [9]. Hence, cloud resources from different locations (e.g. data centers) must be utilized to fulfill adequate response times for geographically-dispersed cloud consumers [8]. In order to tackle these challenges, scheduling approaches should consider distributed cloud resources among different data
centers using distributed processes [6, 9].

There has been extensive research in the area of cloud resource scheduling which considers QoS parameters as optimization constraints [10, 11, 12, 13]. While most research focuses on centralized or hierarchical scheduling schemes, there is a lack of work on decentralized scheduling. In contrast to a centralized or hierarchical scheme, a decentralized setting has no central instance which maintains information of all resources. The information is incomplete and distributed among local nodes [6]. Locally received workloads are either locally scheduled or transferred to remote nodes for achieving better local resource utilization, thus leading to a global load equilibrium [6].

The performance of algorithms solving NP-hard problems decreases rapidly with small increase in input parameters [14. Thus, centralized scheduling approaches using such algorithms are limited in the size of submitted jobs and QoS guarantees like deadlines could not be fulfilled anymore if the amount of jobs submitted increases. Especially in large-scale cloud environments, where the unpredictability and dynamics of resources and workloads are very high, a distributed scheme has better adaptability and scalability compared to centralized and hierarchical systems [6]. It can facilitate the fulfillment of user QoS while increasing the overall system efficiency and reducing cost.

### 1.2 Aim of the Work

Delivering high QoS has become one of the most important factors for cloud providers to stand out against competitors in the market and for being successful in the long term. As the demand for cloud services is ever-growing, it is essential for a cloud provider to be able to keep a high standard of QoS. Especially fast response times are very important for many cloud consumers. For providing a low-latency access for all consumers it is necessary to utilize resources from multiple locations at the same time. This is not possible with classical centralized approaches as they are considering resources only from a single data centre. Using a distributed mechanism, which is able to acquire resources among different data centers can be one solution to this problem.

The main contribution of this thesis is the development of a distributed mechanism for cloud resource scheduling, which considers different QoS requirements of cloud consumers. The QoS constraints should at least include workload execution deadlines as well as execution cost. Incoming workloads could either be executed locally, or forwarded to a remote data centre if the local resource utilization is too high and the workload could not be executed within a user defined deadline. The decision if a workload should be executed locally or not is based on an optimization model, which will be created to represent user QoS guarantees. Different aspects of the expected outcome of this thesis are summarized by the following aspects:

QoS-aware optimization model To make decisions of when and where workloads should be executed, an optimization model has to be developed. This model represents user QoS requirements and should contain at least workload deadlines and execution costs.

Distributed resource scheduling algorithms The main output of this thesis is a decentralized scheduling method which uses a set of algorithms to distribute incoming cloud workloads among different participating nodes (e.g. data centers). Each node makes decisions based on the created optimization model considering QoS constraints, thus leading to an improved overall QoS fulfillment and increased system efficiency.

Evaluation of the approach Using frameworks like CloudSim ${ }^{1}$, the developed approach will be evaluated and compared against centralized approaches. Key metrics like deadline violation rate and cost will be used to measure the performance of the approach especially in large-scale environments with high workload submission rates.

### 1.3 Methodological approach

The methodological approach for this thesis is described by the following paragraphs and can be roughly split up into four parts. The approach consists of both a theoretical model and solution development as well as a practical implementation and evaluation of the developed methods.

Literature review and analysis The first step includes an in-depth analysis of existing approaches targeting cloud resource scheduling. These approaches will be classified into different dimensions like used optimization techniques, architectures, QoS constraints and optimization objectives. Using this classification, existing approaches will be compared with each other and the main differences will be emphasized. Based on the outcome of this analysis, concrete research questions will be deviated which should be answered by this work.

Model development focusing on user QoS Before developing a distributed scheduling technique, cloud resources and workloads as well as QoS requirements have to be mapped onto a model which represents the optimization problem. The model should be aware of the different resource types as well as the different workload types occurring in a cloud environment. It should at least map workload deadlines defined by the user as well as execution cost.

Development of distributed scheduling mechanism The main focus of this thesis will be the development of a distributed workload scheduling algorithm. The algorithm will be used to distribute incoming local workloads across the system. The decision if

[^0]a workload will be executed on a specific node in the system will be made using the developed optimization model which takes care that user QoS constraints will be met.

Implementation and evaluation of the developed approach The developed algorithm and optimization model will be implemented using a cloud simulation framework like CloudSim. Key metrics like deadline violation rate and execution cost will be measured during a simulation of submitted workloads. Other approaches will also be simulated under the same conditions and in the end a comparison will be made to see how efficient a distributed approach is against centralized ones.

### 1.4 Structure of the Work

Chapter 2 starts with an introduction to cloud computing and its basic concepts and mechanics. This includes the definition of the terms Quality of Sercvice and Service Level Agreement and how they are related with each other. In Chapter 2 also some common optimization techniques used for cloud resource scheduling are described and analyzed. Finally, some existing QoS-aware cloud resource scheduling approaches are examined and in the end research gaps are outlined and concrete research questions for this work are formulated.

Chapter 3 provides the proposed approach of this work, which includes a QoS-aware distributed scheduling mechanism. The chapter is split up into two parts. The first part describes the local scheduling problem within in single data center. Therefore a PSO algorithm is utilized in order to map tasks to resources. The second part of the chapter describes a distributed resource discovery approach which aims in finding suitable remote resources within the cloud system which can process a given task. In Chapter 4 a concrete implementation of the proposed approach is presented using the cloud simulation framework CloudSim.

The approach of this work is then evaluated in Chapter 5. Therefore multiple test scenarios are conducted and the approach is simulated using the implementation of Chapter 4. Several user QoS metrics are measured during the simulation and the different scenarios are then compared with each other in order to see how the proposed approach performs against other approaches. Finally, Chapter 6 concludes this work by answering the formulated research questions and summarizing the received results of the evaluation.

## State of the Art

This chapter provides a deeper analysis of concepts and research topics utilized in the further parts of the work. Initially, a very brief introduction to cloud computing and the QoS-aware cloud is presented in Section 2.1. This introduction gives a basic understanding of a cloud environment's architecture and explain why the strategy of running applications in the cloud has already been established very well. It also emphasizes the importance of QoS guarantees and SLAs between cloud providers and individual cloud users. Finally, the section covers principles of autonomic computing and points out rising challenges especially for autonomic computing in the cloud.

Section 2.2 covers the optimization topic in general and cloud optimization specifically. The term cloud optimization describes the autonomic resource scheduling process in the cloud (i.e. allocation of virtual machines for incoming workloads), which also takes user defined QoS parameters into consideration. This section presents some widely used optimization techniques utilized for autonomic resource scheduling, including classical optimization models and evolutionary computation algorithms and heuristics. Also advantages and disadvantages of a centralized optimization strategy especially in cloud environment are discussed. On the other hand concepts of decentralized optimization are presented and it is examined how they could be applied for resource scheduling in a cloud environment.

In Section 2.3 some existing approaches of autonomic resource scheduling in the cloud are analyzed and explained. The aim is to provide a heterogeneous overview of the different techniques used to solve optimization problems.

Finally, Section 2.4 summarizes this chapter and formulates arising research questions, derived from the current state of the art approaches. It outlines open research gaps which are then discussed in the further parts of this work.

### 2.1 QoS-aware Cloud Computing

Cloud computing rapidly changes the way of how software is being developed and consumed. It facilitates a new way of how "users access services based on their requirements without regard to where the services are hosted or how they are delivered" 3]. One of its main characteristics is the ability "to pay for use of computing resources on a short-term basis as needed" 15]. These services and resources are provided by large data centers and accessed using web technologies [16]. Physical resources within the data center are substituted away by many virtual resources and thus computational capacity does no longer depend on the underlying hardware. This concept is also referred to as virtualization [4]. Virtualization allows cloud providers to offer seemingly unlimited virtual resources (e.g. virtual machines) and easily scale these resources if user demands are changing. If the incoming workload is increasing, more virtual resources are allocated (i.e. virtual machines started) and if the workload is going down again, not needed resources are released. This principle of automatically scheduling resources in the cloud adds a great flexibility but also more complexity and challenges when trying to manage resources in an optimized way.

The main motivational driver of cloud computing is economic 16. Cloud providers can offer flexible pricing models such as pay-per-use, pay-per-subscription or pay-pertransaction [17]. This models eliminate up-front costs and commitment of the cloud users and provide them a powerful flexibility for consuming cloud services as their costs scale with their demand. If a user needs more computing resources he can simply acquire them according to his demand and release them when they are not used any more. In the end he only pays for used resources. This scalability combined with a flexible pricing model contributes to growing usage of cloud computing. Examples of large cloud providers are Amazon Web Services ${ }^{11}$, Google Cloud Platform ${ }^{2}$ and Microsoft Azure ${ }^{3}$

### 2.1.1 Quality of Service and Service Level Agreements

When using services from the cloud on a pay-per-use basis it is crucial to ensure that these services are efficiently delivered to the end users. If a user runs an application in the cloud, he needs a guarantee that his application is executed within a predefined deadline for example. This guarantee is described through Quality of Service (QoS). With QoS, delivered services from the cloud can be efficiently monitored and measured [18]. Common end user QoS parameters are Deadline, Budget, Availability and Penalty Rate Ratio [19. The contract between the service provider and the service consumer, which defines the expected level of service is referred to as a SLA (Service Level Agreement) and QoS parameters are typically part of a SLA [20].

[^1]
### 2.1.2 Cloud architecture

The following part briefly demonstrates the general structure of a cloud environment and discusses optimization goals for each component. A cloud computing environment can be divided into four layers: i) the hardware layer, ii) the infrastructure layer, iii) the platform layer and iv) the application layer [21]. Figure 2.1 depicts this layered model graphically. In the infrastructure layer, physical resources such as CPU, storage and memory from the hardware layer are virtualized and packaged as virtual machines. This offering of computing services is called Infrastructure as a service (IaaS). The Platform as a service (PaaS) layer consists of platform services like database servers and software frameworks. This applications are running in virtual machines consumed from the IaaS layer. Finally the Software as a service (SaaS) layer is composed of simple applications which are offered to the end users. This applications are usually deployed in PaaS containers 16.


Figure 2.1: Layers of a cloud environment, based on [21.

Each layer has a different set of objectives to achieve and also a set of constraints impacting this achievement [22]. The following part summarizes the individual optimization goals and constraints for each layer.

## IaaS - Level

Goals: The main goal in the IaaS level is to increase resource utilization, which results in a cost reduction and an increase in the gained revenue.
Constraints: On the one hand there are capacity contracts with the PaaS layer and on the other hand there are limitations based on the available physical resources like processors, memory and storage.

## PaaS - Level

Goals: In order to maximize profit, PaaS owners aim to minimize used resources from the IaaS layer and maximize hosted applications from the SaaS layer.
Constraints: Constraints for PaaS owners are mainly expressed through SLA contracts with SaaS owners.

## SaaS - Level

Goals: The SaaS level provides services which are directly consumed by end users. Hence, the main objective is to provide an adequate QoS for end users.
Constraints: Like the constraints for PaaS owners, SaaS constraints are also expressed through SLA contracts with application end users.

Managing resources in a cloud environment can be done in this three different layers, where each layer has its own set of optimization goals and constraints. This work will focus on scheduling in the SaaS layer, which is also referred to as "scheduling in the application layer" [9]. Scheduling resources in the application layer is about to schedule virtual resources to support user applications with optimal QoS and efficiency [9]. In order to maximize efficiency and allocate resources effectively by optimizing QoS parameters, autonomic cloud computing can be one solution [23], which is also called autonomic resource scheduling in the cloud. This technique is presented in the following part.

### 2.1.3 Autonomic Resource Scheduling

The virtualization technique used in cloud data centers enables great flexibility but also introduces more system management complexity. There are now two levels of mapping which must be considered [24]. This resource mapping is graphically illustrated in Figure 2.2. The first layer has to consider the mapping of hosted applications to appropriate virtual resources (virtual machines). Every application is driven by an individual SLA defining several QoS parameters which have to be fulfilled for that specific application. The main challenge is to map these applications to virtual machines and ensuring that available resources are utilized in an optimal way on the one hand and that all specific QoS requirements for each application can be met on the other hand.

In the second layer, virtual machines must then be mapped to underlying physical resources. This mapping problem is usually driven by a data center's resource management costs and mostly includes the goal of reducing energy consumption to minimize costs [24]. As already mentioned above, this work will focus on the mapping problem between hosted applications and virtual resources with individual user QoS constraints.

There are two main objectives of autonomic resource scheduling. The first objective is scheduling suitable resources for incoming workloads on time to increase resource utilization and the second objective is to ensure that numerous QoS parameters are fulfilled for several incoming workloads [18]. In order to fulfill these objectives, the architecture of an autonomic system usually reflects a feedback loop [25, 26] as illustrated


Figure 2.2: Resource mapping in the cloud, based on [24].
in Figure 2.3. This loop is based on IBM's autonomic model [27] and is composed of four steps: Monitor, Analyze, Plan and Execute (also called MAPE loop). The architecture also contains two interfaces (sensors and affectors) which interact with the rest of the environment. A database is used to store different kind of rules, defined by the administrator of the autonomic system [18].

Sensors are delivering information about the state of resources in the underlying environment such as values of QoS parameters. This information gets observed and collected by the monitor module and is then forwarded to the analyze and plan modules. These modules analyze the given information and then create an execution plan for adequate actions based on the given information and stored rules in the database. With this action plan the system is able to react to changes from the outside, like changing QoS parameters. The actions defined in the plan are then automatically executed by the Executor corresponding to environmental changes [28]. Finally, the new state is transferred to the rest of the system through the affector interface [18].


Figure 2.3: Architecture of an autonomic system (MAPE loop), based on [18, 29].

To sum up, this section first defined the term cloud computing and outlined how cloud computing changes the way of software deployment. Through the virtualization technology, cloud provider are able to offer great flexibility to consumers in terms of computing resources. QoS and SLAs were introduced as tools for defining and monitoring delivered services from the cloud, which is essential for consumers.

The different layers of a cloud architecture were illustrated and their individual optimization goals and constraints were listed. Especially the SaaS was emphasized, as the further research of this work will concentrate on an approach targeting optimization problems within this layer. In order to maximize resource allocation and QoS efficiency, autonomic resource scheduling was introduced. This approach targets the challenge of optimally mapping incoming workloads to appropriate virtual resources under consideration of several QoS parameters. Section 2.2 covers the optimization topic and approaches how optimization methods can be utilized and integrated within autonomic systems and the presented feedback loop.

### 2.2 Optimization in the Cloud

This section introduces some well-known optimization approaches for resource scheduling based on SLAs in general and then presents established optimization methods used in cloud environments for autonomic resource scheduling. Initially the cloud resource scheduling problem is discussed and defined. Models and algorithms for solving such class of problems are presented. This includes heuristics and algorithms from the field of Evolutionary Computation. Finally a state of the art concept is provided which illustrates how optimization can be integrated in cloud environments.

### 2.2.1 Cloud Resource Scheduling Problem

The problem of resource scheduling in the cloud based on SLA is a NP-hard problem [7]. As pointed out in Section 2.1, a QoS-aware cloud has to ensure that QoS parameters like latency and throughput have to be fulfilled as defined in the SLA while also considering an optimal resource usage to minimize costs. This optimal mapping between hosted applications and available resources is a combinatorial optimization problem [30] and takes a significant amount of time to find an optimal solution [7].

The scheduling problem can be divided into two classes: i) static scheduling and ii) dynamic scheduling. In cloud computing resources are heterogenous and always dynamically allocated [31] depending on the current workload. This leads to a dynamic scheduling problem in the cloud which has two factors of uncertainty [32]:

- Workloads are uncertain. It is not known when and how many requests for workloads are coming in.
- Resources are uncertain. Available resources might change over time, depending on current load and other factors.

In contrast to static scheduling, where already known tasks from a foregone environment are prescheduled, dynamic scheduling must also consider the current system state for making an optimal scheduling plan [31. Cloud resource scheduling is about finding the optimal mapping $C: \mathbf{T} \times \mathbf{R} \rightarrow \mathbb{R}^{z}$ which assigns a number of $M$ required tasks $\mathbf{T}=\left\{T_{1}, T_{2}, \ldots, T_{M}\right\}$ (incoming workloads) onto $N$ available cloud resources $\mathbf{R}=\left\{R_{1}, R_{2}, \ldots, R_{N}\right\}$ (virtual machines). The mapping has to consider that the fitness of $z$ given objectives $\mathbf{F}=\left\{F_{1}, F_{2}, \ldots, F_{z}\right\}$ is maximized [9]. These objectives usually include QoS, costs and energy efficiency [9]. Figure 2.4 emphasizes above described problem graphically.


Figure 2.4: Resource scheduling problem in the cloud, based on [9].
There exist several algorithms and heuristics for solving the cloud resource scheduling problem. Many of them are exhaustive in nature and convert the problem into a combinatorial optimization problem such as Linear Programming or Integer Programming. But being an NP-hard problem, cloud resource scheduling can push these approaches to their limits with an increase of optimization variables and dimensionality [9]. Because of the NP-hardness, algorithms from the area of Evolutionary Computation (EC) are one, well-established approach for tackling this problem [33]. EC and important algorithms from this field are discussed in Subsection 2.2.3.

This part provided a mathematical and graphical formulation of the cloud resource scheduling problem. It pointed out the dynamic nature of a cloud environment, like heterogeneous resources and uncertain workloads, as well as arising problems through individual constraints. The next part presents some classical optimization techniques for solving this kind of problems. Afterwards the field of EC is presented, which algorithms are widely utilized in cloud resource scheduling.

### 2.2.2 Optimization Methods

This part introduces some convenient techniques of mathematical programming, utilized for optimization in cloud environments. These concepts conduce to the general methodology applied in further parts of this work.

## Linear Programming (LP)

Linear Programming is a special case of mathematical optimization with the goal of achieving the best outcome of a mathematical model. The requirements within this model are described by linear relationships. It can be applied in various fields, especially in operations research, which also includes scheduling. LP is about optimizing a linear objective function restricted by linear equality and inequality constraints. A LP model can be formulated as following [34]:

$$
\begin{equation*}
\max \sum_{j=1}^{n} c_{j} x_{j}, c \in \mathbb{R} \tag{2.1}
\end{equation*}
$$

under the constraints

$$
\begin{gathered}
\sum_{j=1}^{n} a_{i j} x_{j} \leq b_{i}, i=1, \ldots, m \\
x_{j} \geq 0, j=1, \ldots, n
\end{gathered}
$$

The variable $b \in \mathbb{R}^{m}$ represents the constant part of the constraints and is usually on the right side of the equation. The inequalities have the direction of $\leq$ for maximizations and $\geq$ for minimizations [35]. $c$ and $a$ are known coefficients and $x_{j}$ represents the unknown variables to be determined. A LP model can be solved either graphically or algebraic, whereas the graphical solution is restricted to 2 to 3 variables and therefore not applicable for solving problems occurring in the industry [35]. The feasible region of the objective function is a convex polytope which is graphically demonstrated in Figure 2.5 with two variables. Though it is not guaranteed that an optimal solution exists because of two reasons. First, if two inequalities are inconsistent (e.g. $x>4$ and $x<3$ ) the constraints can never be satisfied and there is no optimal solution. The second reason is, if the polytope is unbounded in the direction of the gradient (vector of coefficients) of the objective function.

In addition to the graphical and algebraic methods, algorithms can be used for solving LP models. A very important algorithm for LP is the simplex algorithm developed by George Dantzig in 1947 [36]. As Figure 2.5 illustrates, the feasible region in a LP problem is a convex polytope. The simplex algorithm now starts by construction a feasible solution at any vertex of the polytope and then moves alongside a path of the polytope to vertices which do not decrease the value of the objective function. This is done until an optimum is reached [36].


Figure 2.5: Feasible region of simple linear program with two variables.

## Integer Linear Programming (ILP)

Integer Linear Programming problems are LP problems where some or all variables are restricted to be an integer. It is known as NP-hard [37]. A special case of ILP problems are Mixed Integer Linear Programming (MILP) problems, where only some of the variables are restricted to be an integer. Especially in many practical problems, variables only make sense when they have integer values [37]. In cloud computing for example, it is necessary to assign virtual machines to given workloads, where the number of virtual machines must be an integer, since virtual machines cannot be divided. Another reason for using ILP models is when the integer variables represent decisions such as yes or no and can only take the values 0 and 1 [37].

ILP problems occur frequently in the industry and can be applied in areas like production planning, scheduling, telecommunication networks and cellular networks [37]. There exist several algorithms for solving ILP problems. One category of them are exact algorithms which are based on solving the corresponding LP relaxation - by removing the integer constraint and solving the LP - first. Classes of such algorithms are cutting plane - and branch and bound methods for example [37].

Since ILP problems are NP-hard, classical methods may be very slow or even fail to find any exact solution for some issues in polynomial time. The computation time strongly depends on the number of integer restricted variables [37]. To solve this kind of problems more quickly, or to find an approximate solution if the classic method fails, heuristic methods can be used. A heuristic is a technique in the area of artificial intelligence and mathematical optimization which should produce solutions for a complex problem in reasonable time. Although the solution may not be the optimal one 38]. Examples of heuristic methods are Hill Climbing, Simulated Annealing and Hopfield Networks.

Especially in the area of cloud computing, a class of heuristic methods has been very well established for solving multi-objective scheduling problems. They belong to the field of Evolutionary Computation and the most important techniques are presented in the following Section 2.2.3.

### 2.2.3 Evolutionary Computation (EC)

The methodology of Evolutionary Computation (EC) "is inspired by the mechanisms of biological evolution and behaviors of living organisms" [39] and aims on solving complex optimization problems. The algorithms associated to the field of EC are also called Evolutionary Algorithms (EA) [40]. Recent work has shown an increasing usage of EC algorithms for improved efficiency and effectiveness in complex cloud systems for resource scheduling [9, 41]. Especially the three algorithms i) Genetic Algorithm (GA), ii) Ant Colony Optimization (ACO) and iii) Particle Swarm Optimization (PSO) have become very popular for tackling cloud resource scheduling problems [9] and will be described later in this section more precisely.


Figure 2.6: A general EC framework, based on [39].
Figure 2.6 depicts a general EC framework which describes three fundamental steps pertaining to most EC algorithm implementations, although each specific implementation may be a little bit different. The general framework also contains two optional steps, which are performed additionally by some algorithms [39]. EC algorithms are a posteriori and nondeterministic in nature [9. The first step of EC algorithms is the initialization phase where starting values and parameters are set. After the initialization phase, algorithms enter an evolutionary iteration where the two operational steps Fitness Evaluation and

Selection and Population Reproduction and Variation are executed. After each iteration the new population is validated against a stop criterion and eventually repeated until the criterion is met [39]. Search information is exchanged among the different solution candidates 9 .

The next part presents the three most important EC algorithms, which are widely utilized in cloud resource scheduling. These heuristics are used to increase efficiency and performance of solving a complex scheduling problem where classical methods may take too long or no exact solution exists.

## Genetic Algorithm (GA)

Genetic algorithms are adaptive methods which may be used to solve search and optimization problems [42]. They "are based on the genetic process of biological organisms" [43. One of the main concepts of EC algorithms is the natural selection, which evolves natural populations over many generations. Genetic algorithms mimic this process and are able to evolve solutions to real world problems [43].

Potential solutions to a problem are represented as a set of parameters, which are also known as genes. These genes are joined together to form a string of values, also called chromosome. Each set of parameters, represented by a chromosome is called individual [43]. Before the algorithm can be run, a fitness has to be assigned to each individual, which is determined by a fitness function [44]. During runtime of the algorithm, individuals are selected from the population and recombined with mechanisms like crossover and mutation [43]. Algorithm 2.1 shows a metaheuristic of the described behavior.

```
Algorithm 2.1: Genetic Algorithm Metaheuristic, based on [43]
    Generate initial population \(P_{t}\);
    Evaluate population \(P_{t}\);
    while stopping criteria not satisfied do
        Select elements from \(P_{t}\) to copy into \(P_{t+1}\);
        Crossover elements of \(P_{t}\) and put into \(P_{t+1}\);
        Mutate elements of \(P_{t}\) and put into \(P_{t+1}\);
        Evaluate new population \(P_{t+1}\);
        \(P_{t}=P_{t+1}\)
    end
```

Figure 2.7 describes the operation of a GA by an example. Each individual of the population consists of a string of binary digits. This is the simplest form of representation and usually GAs use more complex representations for real world problems [42].


Figure 2.7: Operation of the Genetic Algorithm, based on 42].

Given a population of three individuals at time $T_{n}$ as depicted in Figure 2.7, each individual is assigned a fitness value by the function $F$. Based on this fitness values, copies are assigned to each individual during the selection phase. For example, the second individual (11100) is assigned with two copies. After the selection phase, genetic mechanisms like mutation and crossover are applied to recombine the selected individuals. In the end, a new population results from these operations at time $T_{n+1}$.

## Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is a general purpose optimization technique which is inspired from the foraging behavior of some ant species [45]. The mechanism of ACO is based on the fact that ants deposit pheromones on the ground in order to mark a preferential path, which should also be used by other ants in the colony [45]. ACO is a metaheuristic for solving hard combinatorial optimization techniques 46 and there have been proposed many different ACO algorithms solving problems in different research areas. However, all these algorithms are based on the same characteristics, which are presented by Algorithm 2.2.

```
Algorithm 2.2: Ant Colony Optimization Metaheuristic, based on [45]
    Set parameters;
    Initialize pheromone trails;
    while stopping criteria not satisfied do
        ConstructAntSolutions;
        ApplyLocalSearch (optional);
        UpdatePheromones;
    end
```

In analogy to real world ants, in ACO there exists a colony of simple agents, called artificial ants which are mediated by artificial pheromones [45, 46]. These trails are used as an indirect communication medium which serves distributed, numerical information
to each ant in the colony [46]. The metaheuristic shown in Algorithm 2.2 iterates over three phases after initialization. In the first phase, a number of solutions are constructed by the ants. This solutions are then improved through an optional local search, which is highly problem specific [45]. In the last step of the iteration, all pheromones are updated according to the new solutions. The following describes the behavior of a generic ACO algorithm applied to the well known traveling salesman problem.

The traveling salesman problem (TSP) is about finding the shortest tour that allows visiting a given set of cities, where the distance between each city is known and each city must be visited once and only once. For solving this problem with ACO, ants are moving on a graph whose vertices represent cities and whose edges represent the connection between each city. The pheromone is a variable which is associated with each edge on the graph and ants can modify and read this variable. According to the first step of the iteration in the algorithm, each ant builds a solution by walking from vertex to vertex on the graph. Their only constraint is not visiting a vertex they had already been visited before [45].


Figure 2.8: Possible construction graph for a 4-city TSP
An ant selects a vertex to be visited according to a stochastic mechanism, biased by the pheromone. For example the ant is at vertex $i$ and vertex $j$ has not been visited yet, then $j$ can be selected with a probability that is proportional to the pheromone associated with the edge $(i, j)$ [45]. Figure 2.8 shows a possible construction graph for a traveling salesman problem with four cities, where the pheromones are associated with the edges. At the end of each iteration, pheromone values on the edges are updated, based on the solution quality generated by the ants. This modification should bias future ants to construct better solutions.

ACO algorithms are used for solving complex combinatorial optimization problems. Alongside the traveling salesman problem they are also applied for complex scheduling problems and have also found an application for resource scheduling in cloud systems [47.

## Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is an evolutionary optimization method, inspired by intelligent swarm behavior in birds flocking and fish schooling [48, 49]. The social ability of groups of some species of animals (e.g. birds) to work as a whole for finding a desirable location is adapted to perform an optimization search [50]. In PSO particles in the swarm are guided to search for globally optimal solutions [51].

In most common PSO implementations, particles use a combination of the best solution they have found and the best solution that any particle in their neighborhood has found for moving through the search space [50]. Among other topological neighborhoods, the global neighborhood, also known as gbest model has become established in many PSO implementations. In this topology, all particles are connected with each other and are able to obtain information from any particle of the swarm [50.

Each individual particle $i$ is composed of three vectors: the position in the Ddimensional search space $\overrightarrow{x_{i}}=\left(x_{i 1}, x_{i 2}, \ldots, x_{i D}\right)$, the individually found position $\overrightarrow{p_{i}}=$ $\left(p_{i 1}, p_{i 2}, \ldots, p_{i D}\right)$ and its velocity $\overrightarrow{v_{i}}=\left(v_{i 1}, v_{i 2}, \ldots, v_{i D}\right)$. In the initialization phase, the particles are distributed randomly throughout the search space. During the iteration phase the particles move through the search space, based on a simple set of update equations:

$$
\begin{equation*}
v_{i d}=v_{i d}+c \epsilon_{1}\left(p_{i d}-x_{i d}\right)+c \epsilon_{2}\left(p_{g d}-x_{i d}\right) \tag{2.2}
\end{equation*}
$$

$$
\begin{equation*}
x_{i d}=x_{i d}-v_{i d} \tag{2.3}
\end{equation*}
$$

Where $c$ is a constant and $\epsilon_{1}, \epsilon_{2}$ are independent random numbers, which are generated uniquely at every iteration step for each dimension from $d=1$ to $D$. The vector $\overrightarrow{p_{g}}$ represents the best position found by any neighbor of the particle [50]. Algorithm 2.3 shows the whole update process.

```
Algorithm 2.3: PSO update process, based on [50]
    for each time step \(t\) do
        for each particle \(i\) in the swarm do
            update position \(\overrightarrow{x_{t}}\) using equations (2.2) \& (2.3);
            calculate particle fitness \(f\left(\overrightarrow{x_{t}}\right)\);
            update \(\overrightarrow{p_{i}}, \overrightarrow{p_{g}}\);
        end
    end
```


### 2.2.4 Optimization Architecture

The previous parts of this section presented concrete optimization technologies and methods suited for solving complex scheduling problems in cloud environments. In practice, a framework is needed to integrate these techniques in an existing cloud architecture. This part explains a common optimization architecture used for cloud resource scheduling.


Figure 2.9: Feedback control loop architecture, based on [16].
As already discussed in Section 2.1, a feedback loop is suitable for autonomic computing. However, a cloud's performance is strongly time dependent and therefore the feedback loop has to be adaptive, as optimization goals and cloud parameters change over time [16]. Figure 2.9 illustrates a variation of the Model Identification Adaptive Control (MIAC) [16, 52] architecture which can be utilized in cloud environments for optimization and control. This feedback loop is applicable for each different layer in the cloud. Each layer has in- and outgoing edges to other services and layers. Through this interfaces the different layers can communicate with each other. Through sensors each layer can measure important metrics from other layers and services and provide this information to the Model Identification component, which evaluates the current state of the layer and predicts impacts of possible changes. The collected information is represented by a Performance Model which acts as one input of the optimization component [16].

The Optimization $\&$ Control unit makes proactive changes based on the performance model and external goals and policies which influences hardware and software resources. These changes should guarantee an optimal fulfillment of the predefined goals for each layer [16].

### 2.3 Analysis of existing approaches

This section presents and analyzes different existing approaches for cloud optimization with QoS guarantees. These approaches tackle the autonomic resource management problem in the cloud, based on different scheduling criteria. The techniques are categorized by common attributes like objectives and architecture. Because there are so many approaches, only fundamentally different ones are presented and compared to gain knowledge about the various methodologies. For a more in-depth discussion we refer to to the surveys of [18] and [9].

Table 2.1 lists the different approaches and categorizes their used technique (algorithm), the main objective and the chosen solution architecture to solve the scheduling problem. Many existing solutions utilize evolutionary heuristics to solve the NP-hard scheduling problem, but there are also approaches which reformulate the problem into a classical IP problem. Another dimension of differentiation when comparing approaches is the point of view. On one hand, cost and performance can be optimized from the cloud provider's view to increase the overall efficiency. On the other hand, QoS parameters relevant for cloud consumers can be optimized to increase the user satisfaction. The next part introduces approaches considering provider efficiency as well as optimization approaches considering user QoS.

Table 2.1: Selection of different cloud resource scheduling approaches

| Technique | Objective | Architecture | Context | Authors |
| :---: | :---: | :---: | :---: | :---: |
| GA | Deadline, Cost | Centralized | QoS/Provider | Chen et al. 2015 [10] |
| ACO | Energy cost | Centralized | Provider | Liu et al. 2014 [5] |
| ACO | Multiobjective | Centralized | User QoS | Zuo et al. 2015 [53] |
| PSO | Cost | Centralized | User QoS | Li et al. 2015 [1] |
| IP | Deadline, Cost | Centralized | User QoS | Mao et al. 2010 [13] |
| CASA | Performance | Decentralized | Provider | Huang et al. 2013 [12] |

## DOGA

Chen et al. [10] proposed a deadline constrained scheduling approach based on a genetic algorithm. Alongside the deadline constraint, their goal is to minimize execution cost. Therefore they used a cost-minimization and deadline-constrained model introduced by Rodriguez and Buyya [54] in 2014. The model has a great availability and is able to meet business organization requirements [10]. To solve this model they used an improved GA.

To meet tight deadline constraints they proposed a dynamic objective strategy (DOS), where the GA focuses on execution time as objective as long as no feasible solution can be found. When a feasible solution is found, the optimization objective of the GA changes to the execution cost [10]. They name this DOS based GA approach $D O G A$. Figure 2.10 shows the flowchart of the DOGA approach.


Figure 2.10: Flowchart of the DOGA approach, based on [10].

The DOGA approach is compared against an approach [54] which solves the same cost-deadline model using a PSO algorithm. The outcome of the experiment showed that through the adaptive behavior of the GA variable deadlines could be met, with smaller cost than the PSO.

## ACO-VMP

The approach proposed by Liu et al. [5, called ACO-VMP, utilizes an ACO based algorithm to tackle the VM placement (VMP) problem and to reduce the number of running physical servers. The main objective behind this approach is the minimization of total energy consumption and energy cost from a cloud provider's point of view. In contrast to DOGA, where the optimization takes place on workflows assigned to virtual machines, this approach tackles the scheduling problem of assigning virtual machines to physical resources.

They formulate the VMP problem as a combinatorial optimization problem and solve this problem by an ACO-based algorithm. Different from other solutions, their algorithm works in a way that pheromone is placed between every two VMs instead of between the physical server and the VM. In that way, the historical desirability of placing them on the same physical server can be recorded. In the beginning of the ACO-VMP approach the amounts of VMs and physical servers are equal. During each evolutionary process step, the number of physical servers is then set as one less than the number of servers used in the global best solution [5]. This leads to a reduction of physical servers one by one.

The outcome of their experiments showed that this approach is a competitive and effective way of resource utilization, especially when the number of VMs is large.

## PBACO

Zuo et al. [53] proposed a multi-objective optimization method called PBACO, also based on an ACO algorithm. Similar to the DOGA approach PBACO also builds a resource cost model first, which reflects the demands of the tasks for the resources in detail. Resources and tasks in cloud computing are all diverse [53]. Some tasks have high CPU demands while others may require more storage or memory and therefore costs are different for different tasks. In order to reflect this heterogeneity, they built a resource cost model.


Figure 2.11: Framework model of the PBACO approach, based on 53].

In their model, they divided the resource cost into the two parts of CPU $C$ and memory $M$ cost. They used the following definitions for tasks and resources. Tasks: $T_{i}=\left(C_{i}, M_{i}, D_{i}, B_{i}\right)$ where $D_{i}$ represents the deadline of the task and $B_{i}$ the budget cost of the user. Resources: $R_{i}=\left(C_{j}, M_{j}\right)$ where $C_{j}$ is the CPU cost and $M_{j}$ the memory cost, as already defined in the cost model.

Their approach considerd the makespan and the user's budget costs as constraints which leads to a multi-objective optimization of both performance and cost [53]. This differs from the ACO-VMP approach, which only considers the energy cost of the system, regardless of how efficient tasks are scheduled according to their deadline.

Figure 2.11 illustrates the framework model of the PBACO approach. All submitted tasks from users are first handled and processed by the task manager which forwards the information to the scheduler. On the other side, each physical node in the system is monitored by a local resource manager to obtain CPU und memory metrics. A central resource manager collects all information from the local nodes and calculates the cost according to the resource cost model. The core component is the scheduler which is responsible for allocating tasks to resources. It utilizes the ACO based optimization method and the information from the task manager and resource manager to calculate an optimal scheduling plan.

Their test cases showed that PBACO has great advantages regarding the makespan against similar approaches. They argue that considering multiple objectives makes their method more efficient than similar ones using only one objective.

## RNPSO

Similar to the DOGA approach Li et al. (11] proposed an approach which is also based on the cost-minimization and deadline-constrained model from Rodriguez and Buyya [54. However, their optimization method is a different one than DOGA's as they used a renumber PSO (RNPSO) for solving the model instead of a GA.


Figure 2.12: Example workflow in a cloud, based on [11.
They used a particle encoding where each particle has a dimension equal to the amount of tasks in the workflow. For example the workflow shown in Figure 2.12 with nine tasks results in a 9 -dimensional particle with a position determined by the nine coordinates. An example is given in Table 2.2.

Table 2.2: Example encoding of a particle in RNPSO

| $d_{1}$ | $d_{2}$ | $d_{3}$ | $d_{4}$ | $d_{5}$ | $d_{6}$ | $d_{7}$ | $d_{8}$ | $d_{9}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 3.2 | 2.9 | 1.1 | 1.0 | 2.1 | 3.0 | 1.9 | 3.9 | 1.3 |

The ranges of all dimensions are real numbers between 1.0 and the amount of total available resources (e.g. VMs) plus one. Each dimension of a particle also has an integer int value which is derived by rounding down the value of the dimension. For example
$d_{1}$ from Table 2.2 has the integer value 3 . This integer value represents an index and means that task $k_{d}$ is mapped to resource $r_{i n t}$. In the example task $d_{1}$ would be mapped to resource $r_{3}$. RNPSO uses an enhanced PSO algorithm with a renumber strategy. Because IaaS cloud providers offer a large amount of different resource types with random indices in practice, particles do not gain more knowledge during the learning process and thus make the PSO inefficient.

The renumber strategy of RNPSO should tackle this problem by providing a mapping between index 1 and the VM with the lowest cost per unit time. Generally said, they map index $i$ to the VM with the $i$ th lowest cost per unit time. This renumbering adds new information to the index and hence improves the learning process of particles. The rest of the algorithmic process stays the same as in the traditional PSO.

The outcome of their experiment has shown that when using a PSO in a large scale cloud environment, especially with many different types of resources available, the traditional approach is not efficient. They solved this problem by reapplying mappings to the index according to resource properties. In [55] they extended their RNPSO approach to a multi-objective problem (CMPSO) to find non-dominated solutions with different execution cost and time. It is shown that the multi-objective approach outperforms the single-objective one.

## Cloud auto-scaling (CAS)

All presented approaches above are based on heuristics from the field of evolutionary computation. In research there exist also methods which try to solve cloud scheduling with traditional optimization techniques. Mao et al. [13] proposed an approach called Cloud auto-scaling (CAS) which schedules VM instance startup and shut-down activities. In contrast to similar approaches, they also considered the startup time of a VM in the optimization problem because every resource is not immediately available. They formulate their auto-scaling mechanism into several integer programming problems with budget and computing power constraints. These IP problems represent their performance model which is then solved with classical methods like cutting plane and branch and bound.

Figure 2.13 illustrates the architecture of the CAS approach, which they implemented in Windows Azure ${ }^{4}$. The architecture is split into four main components: (i) performance monitor, (ii) history repository, (iii) auto-scaling decider and (iv) VM manager. The performance monitor collects all necessary system information like current workload and job processing time. This information gets committed to the history repository. The VM manager acts as an adapter between their internal architecture and external cloud providers. It hides all specific cloud provider details which should guarantee easy reusability with different cloud providers. The VM manager also updates the history repository with VM startup times and executes the optimal VM schedule, generated by the decider component.

[^2]

Figure 2.13: Architecture of Cloud auto-scaling, based on [13].

The history repository contains all system information as well as historical data which should help the decider predicting future workloads and generating optimal scheduling plans. The core component in the architecture is the auto-scaling decider. Based on the information of the history repository it solves the underlying performance model they formulated and generates an optimal scheduling plan for the VM manager. They are solving the IP problem with Microsoft Solver Foundation ${ }^{5}$.

The outcome of their evaluation showed that the startup time of VMs plays an important role in cloud scheduling, because it could affect performance and cost, especially for very short deadlines. Also choosing an appropriate VM type according to the incoming job can save $20 \%$ to $45 \%$ cost compared to fixed VM types. In future extensions of their approach they are going to extend the performance model into a multi-tier architecture to meet QoS goals at different levels.

## CASA

All above presented approaches are using different techniques for solving scheduling problems in the cloud, but all of them are based on a centralized architecture. To overcome issues such as single point of failure or bottlenecks, a decentralized scheduling scheme is emerging as promising approach [12]. It enables great flexibility and scalability, which are especially in the field of cloud computing, important factors.

[^3][12] proposed a two-phased, dynamic algorithm called Community-aware scheduling algorithm (CASA) which operates in a decentralized manner. CASA is a set of heuristic sub-algorithms which aims on achieving optimal scheduling performance over the whole grid or cloud system instead of a single participating node [12]. In contrast to other approaches, CASA focuses on grid systems, but it is also applicable in clouds. One of the main characteristics of CASA is the design for effectively distributing jobs amongst participating nodes without knowing detailed processing information for each individual node.

The algorithm is split into two phases, the job submission phase and the dynamic scheduling phase. The first part of CASA is the job submission phase. Each time a node receives a job, submitted by a local user it invokes an algorithm which generates a request message containing relevant job information. After that, a special interface is called for finding contactable remote nodes. The request message is then sent to all possible remote notes which could be contacted. The remote nodes then evaluate based on the given job information if they could handle the job and send a respond message. The sender node collects every respond message and then selects one suitable remote node for processing the job.

The second phase of CASA is the dynamic scheduling phase. After submitting and assigning jobs to nodes, each node has a local queue for storing jobs which cannot be executed instantly. Because the state of grid system can change over time without any prediction, already assigned jobs may not be optimal distributed among the nodes within the new state of the grid. Therefore for every job in the local queue of a node, a periodical check is performed. The check aims at finding other nodes which could process the job more efficiently. This dynamic rescheduling is based on the same steps as the submission phase and should ensure optimal efficiency of the system, even if the state changes.

They showed that the decentralized architecture is not only able to accomplish the same number of jobs as a centralized one, but also improved average job slowdown and average job waiting time dramatically. In future work they will extends this approach by implementing it also in current developments of cloud computing.

### 2.4 Research Questions

This sections summarizes the current state of the art for cloud resource scheduling, presented in Section 2.3. It outlines existing research gaps and deviates concrete research questions from these gaps, which should be answered by this thesis.

Table 2.1 categorizes the presented approaches within different dimensions. One distinction is the context of the optimization goal. There are two relevant sides which are considered by most research work. On one hand there is the provider view, which tries to optimize system efficiency, performance and cost. On the other hand there is the cloud consumer view, which mainly tries to optimize resource scheduling considering QoS like deadlines or availability.

Another dimension is the optimization objective. Most research works are considering cost and performance as main objectives [10, 11, 12, 13], which are indeed very important factors in the industry. But also user QoS is emerging as an important optimization objective for many cloud providers. The last dimension is the provided type of solution architecture. There is many research work on centralized or hierarchical schemes, but a lack of work in decentralized approaches. There are approaches which present decentralized scheduling algorithms for grid systems [12], but when it comes to cloud systems, especially in combination with user QoS as optimization objective, more research needs to be done.

The deployment of cloud resources is often distributed among different data centers [56] and cloud users can also be from all over the world. Therefore it would be efficient to schedule resources in data centers which are close to their consumers [9]. This requires also distributed processes. But also other current challenges in cloud computing would benefit from distributed scheduling, like large-scale scheduling and realtime scheduling [9].

Based on the current work for QoS-aware cloud scheduling analyzed in Section 2.3, decentralized QoS resource scheduling has been identified as emerging research direction for the future [9, 18]. This work contributes to this research direction and therefore following research questions can be deviated from existing gaps:

## i "How can local and global requirements be combined during QoS-aware cloud resource collection in a distributed system?"

The proposed approach should consider QoS requirements from the cloud user, which at least should include deadline and cost. These requirements are expected to be fulfilled by the processing data center. To meet the deadline constraint response times between user and data center should be low. This could be achieved when submitted jobs are scheduled in a data center which has an appropriate geographic location with respect to the users location. The goal is to combine these local requirements for a data center with the global requirement in choosing the right data center for reducing response times to the user and satisfying the deadline constraint.
ii "How can QoS-aware cloud resource scheduling be realized in a distributed way?"

The main focus of this work lies on developing an approach which should enable cloud resource scheduling among multiple data centers in a cloud system. Therefore not only local resources but also information about other resources in the system must be observed in order to make an optimal decision in minimizing cost.
iii "How does distributed QoS-aware cloud resource scheduling perform compared to centralized approaches?"

In order to measure the performance and QoS violation of distributed scheduling, the approach should be compared to centralized approaches which utilize only local resources. The goal is to measure the influence of distributed scheduling on deadline constraint and the total execution cost.

# Optimization Scheduling Approach 

### 3.1 Problem Definition and System Model

This section gives an introduction into the problem domain and describes the definition of tasks and resources used for the optimization problem. It defines also the assumed cloud system model and declares the used notation of variables. A main assumption of the proposed approach is the distributed system model which considers not only one data center where workloads are scheduled, but multiple, geographically distributed data centers collaborating to efficiently schedule incoming workloads based on their location to reduce response times. In order to describe the geographically-dispersed cloud consumers as well as the data centers, the task and resource definitions are extended with variables which represent these characteristics. The problem definition is first introduced by constructing a motivating scenario in order to describe the problem domain. The following part then describes the local characteristics of tasks and resources within a data center and then extends this description with global aspects and definitions to model distributed characteristics of the system.

### 3.1.1 Motivating Scenario

Assume a cloud system which consists of multiple data centers, owned by cloud providers and distributed all over the world. Each data center contains a set of resources (i.e. virtual machines) and these resources have a limited capacity of memory and CPU. The purpose of these data centers is to process computational tasks (i.e. execution of a specific service), submitted by cloud users. A cloud user could be any person who wants to execute a service or a program in a data center. These tasks demand resources like memory in order to be processed. Apart from the functional requirements, a task could


Figure 3.1: Example cloud resource scheduling scenario.
also have non-functional requirements which are called $Q o S$ requirements. These may include that the task should be processed until a specified deadline and the processing cost should not exceed a predefined budget. The QoS requirements are usually defined in contracts between cloud user and cloud provider which are called Service Level Agreements (SLAs).

In order to meet functional and non-functional requirements of submitted tasks, a data center has to use a scheduling technique which maps incoming tasks to available resources. The scheduling technique usually has a specific optimization goal described by an internal optimization model. A common optimization goal of cloud resource schedulers is the minimization of the total processing cost. This optimization may be constrained by the individual task's QoS requirements, for example the satisfaction of execution deadlines.

We assume for this work a scenario as depicted in Figure 3.1, where a cloud user could submit a task to any data center in the cloud system. The cloud user is located at a specific geographical location. The data centers also have specific locations. The cloud user has a contract with the cloud provider where task deadlines and task budgets are specified. Each data center uses a resource scheduler which schedules incoming tasks based on the data center's optimization model. The objective function is the minimization of processing cost under the budget and deadline constraints. The formal optimization model is defined and described in Section 3.2,

But often a cloud user and the data center which should process tasks of the user are not in the same geographical region. Figure 3.1 shows an example where an European cloud user submits a task to an Asian data center. With regards to the deadline constraints for tasks, this is often not efficient, as response times may increase due to the large physical distance between the two participants. The response time is the sum of the processing time of a task at a data center and the transfer time of the task from the user to the data center. This relation is shown in Equation 3.1.

$$
\begin{equation*}
\text { ResponseTime }=\text { ProcessingTime }+ \text { TransferTime } \tag{3.1}
\end{equation*}
$$

In order to avoid scheduling tasks from consumers in a different location, a data center's scheduler has to check if there are other data center's in the same region as the user comes from. Therefore the resource scheduling is divided into two phases:
(i) resource discovery phase and (ii) scheduling phase. In the resource discovery phase, the scheduler takes the incoming task and creates a task wrapper. A task wrapper contains information about the original task and additional meta data like the required location. This wrapper is then forwarded to other known data centers as shown in Figure 3.1. If a data center can schedule the task contained in the wrapper and is in the same region as the cloud user, it responds to the requesting data center with a task wrapper response.

The requesting data center collects all task wrapper responses and adds the responding data centers as possible resources to the available resource list. After collecting all task wrapper responses the resource discovery phase is finished and the actual scheduling phase starts. In this phase the task will be mapped onto a suitable resource, based on the optimization model. This resource could either be located locally on the current data center or on a remote data center which was added during the resource discovery phase. The next section provides a formal definition and notations for the presented concepts in this motivation scenario, which are then used in the rest of this work in order to solve the scheduling problem.

### 3.1.2 Definition of Tasks and Resources

First it is assumed that there are $F$ data centers $D=\left\{D_{1}, D_{2}, \ldots, D_{F}\right\}$ in the current cloud system. In each data center there are $K$ tasks $T=\left\{T_{1}, T_{2}, \ldots, T_{K}\right\}$ and $N$ resources $R=\left\{R_{1}, R_{2}, \ldots, R_{N}\right\}$, where resources are assigned to virtual machines and tasks are submitted by cloud consumers. A task is defined with the following properties $T_{i}=\left(B_{i}, D L_{i}, L_{i}, S e_{i}, M_{i}\right) . B_{i}$ describes the budget for the task, defined by the user. The second parameter $D L_{i}$ represents a given deadline until which the task should be executed. These first two parameters are necessary for monitoring the required QoS constraints that all tasks should be executed within their given deadlines and the cost for doing this should not exceed the given budget. The parameter $L_{i}$ describes the estimated length of the task, which is given in million instructions and parameter $S e_{i}$ defines a service requested by the task. All tasks are assumed to be workloads, which are - compared to workflows - independent of their execution order. The last parameter describes the memory usage $M_{i}$ of the task and is also considered to be defined by the submitting user. Task properties like length and memory usage could also be determined by using historical values.

A resource is defined by the following parameters $R_{j}=\left(C_{j}^{C a p}, M_{j}^{C a p}, C_{\text {Cost }}^{j}, M_{\text {Cost }}^{j}, S_{j}\right)$. The first two parameters describe the CPU capacity $C_{j}^{C a p}$ and the memory capacity

Table 3.1: Notation of variables and definitions

| Symbol | Definitions |
| :---: | :--- |
| $K, N, F$ | Number of tasks, resources and data centers in the system |
| $T_{i}$ | The task $i, 1 \leq i \leq K$ |
| $T W_{i}$ | The task wrapper $i$ |
| $T W R_{i}$ | The task wrapper response $i$ |
| $R_{j}$ | The resource $j, 1 \leq j \leq N$ |
| $D_{n}$ | The data center $n, 1 \leq n \leq F$ |
| $S e_{i}$ | Requested Service of task $T_{i}$ |
| $M_{i}$ | Memory usage of task $T_{i}$ |
| $B_{i}$ | Budget of task $T_{i}$ |
| $D L_{i}$ | Deadline of task $T_{i}$ |
| $L_{i}$ | Estimated length of task $T_{i}$ in million instructions |
| $C_{j}^{C a p}$ | CPU capacity of resource $R_{j}$ |
| $M_{j}^{C a p}$ | Memory capacity of resource $R_{j}$ |
| $\tau$ | Billing Time Unit, given in minutes |
| $C_{C o s t}^{j}$ | CPU cost of resource $R_{j}$ for time period $\tau$ |
| $M_{\text {Cost }}^{j}$ | Memory cost of resource $R_{j}$ for time period $\tau$ |
| $S_{j}$ | Processing speed of one CPU on resource $R_{j}$, given in $M I P S$ |
| $P T_{T_{i}}^{R_{j}}$ | Estimated processing time for task $T_{i}$ on resource $R_{j}$ |
| $Z^{T_{i}}$ | Location of the cloud user which submitted task $T_{i}$ |
| $Z^{D_{n}}$ | Location of the data center $D_{n}$ |
| $H^{\text {max }}$ | Maximum depth level of a task wrapper message |
| $H$ | Current depth level of a task wrapper message |
| $T T$ | Current accumulated transfer time of task wrapper message |
| $E E C_{D_{n}}$ | Estimated execution cost of a task on data center $D_{n}$ |
| $E E T_{D_{n}}$ | Estimated execution time of a task on data center $D_{n}$ |

$M_{j}^{C a p}$ of the resource. The second two parameters describe the cost of CPU usage and memory usage respectively. The usage cost of CPU and memory are given by time period $\tau$, which means for example if $\tau=60 \mathrm{~min}$, a user has to pay the given cost $C_{\text {Cost }}^{j}$ for 60 $\min$ usage of one CPU on the resource. $\tau$ is assumed to be the minimum time period for the usage of a resource (i.e. the Billing Time Unit). This means if a CPU is used for 61 $\min$ and $\tau=60 \mathrm{~min}$, the user will be charged for two periods. The last parameter $S_{j}$ defines the speed of one CPU on the resource and is given in Million Instructions per Second (MIPS). Given this information, an estimated processing time of a task $T_{i}$ on resource $R_{j}$ could be calculated: $P T_{T_{i}}^{R_{j}}=\frac{L_{i}}{S_{j}}$.

A task wrapper message is a tuple with the following properties: $T W_{i}=\left(T_{i}, Z^{T_{i}}, H^{\max }, H, T T\right)$. First, it contains the original task $T_{i}$ submitted by the user. The wrapper also contains information about the cloud user's location $Z^{T_{i}} . H^{\max }$ describes the maximum depth level a task wrapper could be forwarded (e.g. if $H^{\max }=2$,


Figure 3.2: Local system model of a data center.
the task wrapper could be forwarded to at most two data centers on a path). Respectively denotes $H$ the current depth level of the task wrapper. $H$ gets incremented each time a task wrapper passes a new data center during the resource discovery phase. TT contains the accumulated transfer time of the task wrapper (i.e. the time it takes to transfer the task from the user to the data center) and gets also updated during the resource discovery phase.

A task wrapper response message is defined by the following parameters: $T W R_{i}=$ $\left(T W_{i}, E E C D_{n}, E E T_{D_{n}} D_{n}\right)$. It wraps the received task wrapper and contains additional information of local resources. First, $D_{n}$ describes the data center the response comes from. The parameter $E E C_{D_{n}}$ describes the estimated execution cost and $E E T_{D_{n}}$ the estimated execution time of the task $T_{i}$ contained in $T W_{i}$ if it would be scheduled on the responding data center $D_{n}$. Table 3.1 summarizes above described definition and the notation of the used symbols.

### 3.1.3 The System Model

The system model is divided into two parts. The first part describes the assumed system framework within a given data center (e.g. the local view). The second part then abstracts away local definitions and presents a global view on the distributed system with different, geographically-dispersed data centers. Figure 3.2 shows the system model of a single data center.

Each data center contains four core components. The Local Resource Manager is responsible for scheduling incoming workloads (tasks) to the available resources (virtual machines). The scheduling is based on a Resource-Cost Model which defines user QoS requirements like cost and deadlines. Incoming workloads are queued up in a task queue first and are then selected by the resource manager for scheduling. The last component


Figure 3.3: Global system model.
is represented by the available resources of the data center. The resource manager is also responsible for monitoring the current load of the data center as well as the resource utilization.

The global system model is illustrated in Figure 3.3. The system consists of several data centers which are geographically distributed all over the world. It is modeled as a graph and every data center is connected with each other. The data centers are grouped into different regions, which could be for example the continents. Also, the cloud users are grouped into this regions. Figure 3.3 illustrates this grouping of data centers and users. The internal model of each data center corresponds to the model described above and presented in Figure 3.2 . Each user can submit tasks to any data center in the system, but the goal is to schedule the user's tasks in a data center which is located in the same region as the user in order to meet the deadline constraint.

The communication between data centers is handled by the local resource managers. They have complete local information about the current workload and resource utilization and can share this information with other data centers. The resource managers are also responsible for task distribution among the data centers in the system. Therefore they execute different algorithms to assign and submit tasks to other data centers or take over incoming tasks. The used algorithms and heuristics are described later in this chapter.

### 3.1.4 Geographic Extension

In order to describe a distributed optimization problem, the initial definition of tasks and resources presented above must be extended with location parameters. $Z^{T_{i}}$ describes the location of the user of task $T_{i}$ and $Z^{D_{n}}$ describes the location of data center $D_{n}$. This information is used by a resource discovery approach to find data centers in the same region as the user. The condition $Z^{T_{i}}=Z^{D_{n}}$ must be fulfilled when task $T_{i}$ is scheduled in data center $D_{n}$ and ensures that the task of the user is scheduled on a data center in the same region as the user. Users could submit their tasks to any data center in system, but this extension facilitates finding the right data center which reduces effectively response times.

A resource discovery algorithm will be presented later in this chapter along with algorithms to distribute tasks among different data centers in the system. But before global requirements are considered, the next part approaches the local optimization model first, which is used by every data center locally to schedule incoming tasks accordingly to meet user-defined QoS constraints like deadline and cost. Based on this local model, each data center also decides if it can handle additional tasks coming from other data centers.

### 3.2 Local Optimization

Before tackling the distributed resource scheduling problem among different data centers in the system, the local optimization and task scheduling is approached first in this section. Therefore, an optimization model is constructed which is utilized by the local resource manager to ensure that the user-defined deadline and cost requirements are met during resource scheduling. The output of this model is a schedule which contains a set of tasks, a set of resources and a mapping $M$ between tasks and resources $M_{T_{i}}^{R_{j}}=\left(T_{i}, R_{j}, S T_{T_{i}}, E T_{T_{i}}\right) . S T_{T_{i}}$ and $E T_{T_{i}}$ are the expected start and end execution times of task $T_{i}$ and are related to the estimated execution time in the following form: $E T_{T_{i}}^{R_{j}}=E T_{T_{i}}-S T_{T_{i}}$. Figure 3.4 shows an example of a generated schedule where incoming tasks are mapped to available resources in a specific time range. It is assumed that each resource can handle only one task at a time.

The execution cost $E C_{T_{i}}$ for a task $T_{i}$ scheduled on a resource $R_{j}$ is defined in Equation 3.2.

$$
\begin{equation*}
E C_{T_{i}}=\left(C_{\text {Cost }}^{j}+\left(M_{\text {Cost }}^{j} \cdot M_{i}\right)\right) \cdot\left\lceil\frac{E T_{T_{i}}^{R_{j}}}{\tau}\right\rceil \tag{3.2}
\end{equation*}
$$

The CPU and memory cost are multiplied accordingly with the assigned CPU and memory usages of the task to get the base usage cost of these resources. The result is then multiplied with the estimated execution time of the task on the resource, divided by the accounting period for resource usage to get the total cost the task causes when scheduled on resource $R_{j}$. The cost factor is rounded up to ensure that only fill billing
time units are accounted. In order to get the total execution cost $T E C_{D_{n}}$ of all tasks on a data center $D_{n}$, the execution costs are summed up, which is shown in Equation 3.3.

$$
\begin{equation*}
T E C_{D_{n}}=\sum_{i=1}^{K} E C_{T_{i}} \tag{3.3}
\end{equation*}
$$

### 3.2.1 QoS-aware Optimization Model

With the equations defined above and other definitions from Section 3.1, a QoS-aware optimization model can be formulated which considers the user's budget and the required task deadlines. The overall (local) optimization goal is to minimize the total execution cost $T E C$ while fulfilling the deadline constraints of the tasks.

$$
\begin{equation*}
\operatorname{minimize}\left(T E C_{D_{n}}\right) \tag{3.4}
\end{equation*}
$$

subject to:

$$
\begin{gather*}
E T_{T_{i}} \leq D L_{i}  \tag{3.5}\\
\sum_{i=1}^{K} E C_{T_{i}} \leq \sum_{i=1}^{K} B_{i} \tag{3.6}
\end{gather*}
$$



Figure 3.4: Example of a generated schedule for incoming tasks.

The two constraints 3.5 and 3.6 ensure that the execution time of each task does not exceed the defined deadline and the scheduling cost for a task does not exceed the fixed task budget. The optimization objective is to minimize execution cost for all tasks, but with the budget constraint it is ensured that the cost are at most as high as the fixed budget. $E T_{T_{i}}$ is referred to the end execution time of task $T_{i}$ and should not be greater than the deadline $D L_{i}$ for the task.

The model is utilized by the resource manager to calculate an optimal task schedule, while guaranteeing user QoS. Since this optimization problem is non-trivial to solve, a heuristic approach is used and presented in the following part.

### 3.2.2 Local Resource Scheduling

To solve the local optimization problem, an algorithm based on the particle swarm optimization (PSO) metaheuristic will be used. The basic concepts of this metaheuristic were already introduced in Chapter 2. A population is used which consists of particles representing candidate solutions of the problem. The particles iteratively move around the search space, influenced by their best local known position and better positions found by other particles. PSO makes no assumptions about the problem space and also not about how good a found solution is. In order to use it for the task scheduling problem, a problem encoding must be defined accordingly. Also a fitness function must be defined to determine the "goodness" of a particle's position.

Each particle $i$ is associated with a position vector $\overrightarrow{x_{i}}$ and a velocity vector $\overrightarrow{v_{i}}$, which together indicate the particle's state. The best solution found by a particle so far is denoted as pbest and the best global solution, which is the best pbest of all particles, is denoted as gbest. Equations 3.7 and 3.8 define how the velocity and position vectors of each particle are updated during an iteration step.

$$
\begin{gather*}
\overrightarrow{v_{i}}(t+1)=\omega \cdot \overrightarrow{v_{i}}(t)+c_{1} \epsilon_{1}\left(\text { pbest }_{i}-\overrightarrow{x_{i}}(t)\right)+c_{2} \epsilon_{2}\left(\text { gbest }-\overrightarrow{x_{i}}(t)\right)  \tag{3.7}\\
\overrightarrow{x_{i}}(t+1)=\overrightarrow{x_{i}}(t)+\overrightarrow{v_{i}}(t) \tag{3.8}
\end{gather*}
$$

The calculation of the new velocity contains several parameters which affect the performance and convergence of the algorithm. $\omega$ denotes the inertia factor or the weight of the previous velocity and is crucial for the algorithm's convergence. $c_{1}$ and $c_{2}$ are constants and can lead to a faster convergence if properly tuned. $\epsilon_{1}$ and $\epsilon_{2}$ are random numbers between 0 and 1 . The coefficient $c_{1} \epsilon_{1}$ defines how much the previous best position of the particle matters for the new velocity, whereas $c_{2} \epsilon_{2}$ determines the weight of the best position found by the particle's neighbors. How these parameters will be set is described in Chapter 5, when preparing an experimental setup.

Algorithm 3.1 describes the process of the used PSO. In a first step, an initial population of particles is set up at a random position and with random velocities. After
that the fitness value for each particle in the population is calculated. The calculation of the fitness value depends on the above defined optimization model and is described in the following part. The fitness value is compared with the particle's previous best position pbest and if the fitness value is better it becomes the new pbest. After checking the pbest, it is compared with the global gbest and if the current particle's pbest value is better than gbest, then it is set as new gbest. In the end the position and velocity of the particle are updated according to above defined Equations 3.7 and 3.8 . The iteration is repeated until a stopping criterion is met.

With the general algorithm defined, the problem must be encoded first to fit into the cloud resource scheduling domain. We use a particle encoding strategy similar to RNPSO from [11]. The main difference is that the approach in [11] uses workflows, whereas the approach in this work assumes workloads. In the context of this work a particle represents one task and the particle's position is described by a single number. An example encoding is shown in Table 3.2 where six particles (i.e. tasks) are displayed with their coordinates. The coordinates describing a particle's position must be a real number between 0 and the total number of resources available. The integer part of this number (i.e. rounded down) describes an index which is related to an available resource, the decimal place will be ignored. In this way, the particle's position describes a mapping from a task to a resource. Following the example given in Table 3.2, particle $p_{1}$ representing task $t_{1}$ has the coordinate 3.2 which would be the integer number 3 and corresponds therefore to resource $r_{3}$. If two tasks are mapped onto the same resource, e.g. $p_{1}$ and $p_{6}$ to resource $r_{3}$, then one task has to wait until the other task is processed. This could be fine if the deadline of the waiting task is still satisfied, but the deadline could also be violated which results in an infeasible solution. Table 3.3 shows the derived task to resource mapping from the example above.

The idea behind this encoding is now to generate a schedule out of the particle positions at each iteration step. Because each particle defines a task to resource mapping,

[^4]Table 3.2: Example encoding of particles.

| $p_{1}$ | $p_{2}$ | $p_{3}$ | $p_{4}$ | $p_{5}$ | $p_{6}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 3.2 | 2.9 | 1.1 | 1.0 | 2.1 | 3.0 |

Table 3.3: Task to resource mapping.

| $t_{1} \rightarrow r_{3}$ | $t_{2} \rightarrow r_{2}$ | $t_{3} \rightarrow r_{1}$ | $t_{4} \rightarrow r_{1}$ | $t_{5} \rightarrow r_{2}$ | $t_{6} \rightarrow r_{3}$ |
| :--- | :--- | :--- | :--- | :--- | :--- |

it is possible to calculate the total execution cost for this schedule. The schedule contains a set of resources processing the tasks, a task to resource mapping, a set of execution times and a set of execution costs for each task. The optimization objective of the QoS-aware model defined in Equations $3.4,3.5$ and 3.6 is the total execution cost of the schedule. Therefore the fitness function of the PSO algorithm is set to the total execution cost and will be minimized.

At each iteration step a schedule will be generated and the resulting total execution costs are compared with each other. But the optimization model also has some constraints like the deadline and budget restrictions for each task. PSO was not designed to handle constrained optimization problems, therefore the constraints must be considered using another strategy. The optimization constraints are considered during a comparison between two solutions and help to determine the better one. Following rules are applied to select a solution:

1. If both solutions are feasible, the one with the better fitness value is selected (i.e. lower total execution cost).
2. If one solution is feasible and the other one infeasible, the feasible one is selected.
3. If both solutions are infeasible, the one with the smaller constraint violation is selected.

A solution is feasible if no constraints are violated. If both solutions are infeasible and violate some constraints the one with the "smaller" violation is selected. This is the case if for example both solutions violate the deadline constraint but only one violates the budget constraint. In such a situation the latter one will be selected as it fulfills at least one constraint. In order to check if a solution is feasible, two metrics are introduced which measure the deadline violation and budget violation numerically.

These metrics are called Deadline Violation Rate $D V_{S}$ and Budget Violation Rate $B V_{S}$ of a schedule $S$ and are defined in Equations 3.9 and 3.10.

$$
\begin{equation*}
D V_{S}=\sum_{i=1}^{K} \max \left\{E T_{i}-D L_{i} ; 0\right\} \tag{3.9}
\end{equation*}
$$

$$
\begin{equation*}
B V_{S}=\sum_{i=1}^{K} \max \left\{E C_{T_{i}}-B_{i} ; 0\right\} \tag{3.10}
\end{equation*}
$$

A solution is feasible if both $D V_{S}$ and $B V_{S}$ are zero, which means that no task in the generated schedule $S$ exceeds its deadline nor its budget. The higher $D V_{S}$ or $B V_{S}$ are, the greater is the violation of the two constraints respectively. In case of two infeasible solutions, the one with the smaller violation rates will be selected. The overall violation consists of a weighted sum of both individual violation rates whereas the deadline is weighted more than the budget. This means if two infeasible solutions are compared which violate both every constraint, the one with the smaller deadline violation is preferred. Because the optimization objective is anyway the total execution cost the budget violation is weighted less in the constraints. The overall violation $V_{S}$ of a schedule $S$ is defined in Equation 3.11.

$$
\begin{equation*}
V_{S}=\rho \cdot D V_{S}+(1-\rho) \cdot B V_{S} \tag{3.11}
\end{equation*}
$$

$\rho$ defines the weight of the two individual constraints and is a number between 0 and 1. A concrete value of $\rho$ will be defined during evaluation in Chapter 5. The result of this formula $V_{S}$ will be used to decide in the end which solution, respectively which position should be selected as the new pbest for a particle.

## Schedule Generation

Algorithm 3.2 shows the pseudo-code of a schedule generation out of the particle positions. It takes as input a set of tasks $T_{i}$ to schedule, an initial pool of available resources and an array which contains the current particle positions. Each particle in the array represents a task, where the particle with index $j$ refers to task $T_{j}$. It outputs a schedule $S$ which contains a task to resource mapping $M$ as well as the overall violation $V_{S}$ and the total execution cost $T E C_{S}$ of the generated schedule. Based on this output, a comparison as described above can be made. At first the sets for used resources and the mapping are initialized as empty in line 1. In order to handle the processing time for tasks on resources, a helper variable called lease-end-time $L E T_{j}$ is introduced which indicates the time when resource $j$ is again ready to process a task. At the beginning, this time is set to 0 for each resource, as all resources are available and no task is scheduled yet.

After the initialization, the algorithm iterates over each position in the array of particle positions and updates the mapping $M$ as follows. First of all, it determines the resource $R_{j}$ to which the particle position $p_{i}$ belongs to by calculating the integer value of the position in line 3. Next, it estimates the processing time of task $T_{i}$ on resource $R_{j}$ based on the assigned CPU usage and length of the task, as well as the CPU-speed of resource $R_{j}$ in line 4. After that, it set the start execution time $S T_{i}$ of the task in line 5. The start time of the task depends on the resource's utilization and if there are

```
Algorithm 3.2: Schedule Generation
    input : A set of K tasks \(T_{i}\), resource pool, array with particle positions
    output:A schedule \(S\) with task to resource mapping
    \(R=\emptyset, M=\emptyset, L E T=0 ;\)
    for \(i=0\) to \(i \leq K-1\) do
        \(j=\left\lfloor p_{i}\right\rfloor ;\)
        \(P T_{i}^{j}=\frac{L_{i}}{S_{j}}\);
        \(S T_{i}=L E T_{j} ;\)
        \(E T_{i}=P T_{i}^{j}+S T_{i} ;\)
        \(L E T_{j}=E T_{i} ;\)
        \(m_{i}^{j}=\left(i, j, S T_{i}, E T_{i}\right) ;\)
        \(M=M \cup\left\{m_{i}^{j}\right\} ;\)
        if \(j \notin R\) then
            \(R=R \cup\{j\} ;\)
        end
        \(E C_{T_{i}}=\left(\left(C_{\text {Cost }}^{j} \cdot C_{i}\right)+\left(M_{\text {Cost }}^{j} \cdot M_{i}\right)\right) \cdot\left\lceil\frac{E T_{T_{i}}^{R_{j}}}{\tau}\right\rceil\)
    end
\(15 T E C_{S}=\sum_{i=1}^{K} E C_{T_{i}}\);
\({ }^{16} D V_{S}=\sum_{i=1}^{K} \max \left\{E T_{i}-D L_{i} ; 0\right\}\);
\({ }_{17} B V_{S}=\sum_{i=1}^{K} \max \left\{E C_{T_{i}}-B_{i} ; 0\right\}\);
\(18 V_{S}=\rho \cdot D V_{S}+(1-\rho) \cdot B V_{S}\);
```

already other tasks assigned, it can not start immediately. This utilization is represented with the lease-end-time of the resources and therefore the start time of the task $S T_{i}$ is set to the time when the resource is ready to use again, i.e. $L E T_{j}$. After setting the start execution time of the task, the estimated end execution time $E T_{i}$ is calculated in line 6 , which is simply the estimated processing time $P T_{i}^{j}$ added to the start time. The lease-end-time for resource $R_{j}$ is updated accordingly to the end time $E T_{i}$ of the newly added task in line 7.

Finally a new mapping $m_{i}^{j}$ is added to the set of mappings in lines 8 and 9 which contains the task $T_{i}$, the resource $R_{j}$ on which the task should be scheduled and the start and end execution times for task $T_{i}$ on resource $R_{j}$. The mapping also contains the execution cost $E C_{T_{i}}$ which are additionally calculated by the algorithm. It also checks if resource $R_{j}$ is already in the set of used resources $R$ and adds it if not in line 11. After


Figure 3.5: Flowchart of the local scheduling approach.
iterating over each particle, the algorithm calculates the fitness value, described as the total execution cost $T E C_{S}$ according to Equation 3.3 , as well as the deadline violation $D V_{S}$, the budget violation $B V_{S}$ and the overall violation $V_{S}$ of the generated schedule $S$ in lines 15 to 18 .

Figure 3.5 summarizes the whole local scheduling approach as flowchart. First, a population based on the incoming tasks is initialized with random positions. Then, the following steps are executed within a loop until a stopping criterion is met. First, a schedule is generated based on the position of the particles. This generation is handled by Algorithm 3.2 as defined above. Then pbest and gbest are updated based on the rules defined above. Therefore, the fitness values and violation rates are compared. After this, the particle positions are updated based on Equations 3.7 and 3.8. In the end, there should be a schedule with minimal total execution cost which (nearly) fulfills the QoS constraints required by the user. The two local algorithms (PSO and schedule generation) are handled and executed by the resource manager. A concrete implementation of the local scheduler is provided in Chapter 4. In order to handle the distributed scheduling between different data centers to minimize response times, the resource manager must also implement distributed mechanisms. These are introduced in the following section.

### 3.3 Distributed Scheduling

The previous section approached the local scheduling problem within a single data center with respect to budget and deadline requirements defined by the cloud user. It does not consider problems which could arise if a cloud user submits tasks to a data center in a completely different region as the user is. A consequence of this could be the increasing of response times between the data center and the user, which also influences the deadline constraint because more time is needed to transfer the task. But users often do not know which data center is the nearest based on their own location, or there exist no data centers in the same region from a specific provider. In order to reduce response
times between cloud consumer and data center, a distributed scheduling approach must ensure that incoming tasks are scheduled to an appropriate data center in the same geographical region as the user. This scheduling is done on a global level and helps to reduce response times.

We assume the system model depicted in Figure 3.3. There are multiple data centers and cloud users in the system, which are grouped into different geographical regions. Figure 3.6 shows a flowchart with the principles of the global scheduling approach. The execution steps are considered to be local, within the context of a single data center. Moreover, these steps are all handled by the local resource manager of a data center. The whole process is triggered when a local resource manager receives a new task, submitted by a user. After receiving a task, the resource manager starts a resource discovery algorithm to find other data centers in the system. The details of this algorithm are presented later in this section, but the main focus lies on finding data centers in the same region as the submitting user. The local resource manager therefore wraps the incoming task from a user in a Task Wrapper $T W_{i}$ and sends this wrapper to other data centers he knows. During this process, the resource manager collects incoming Task Wrapper Responses $T W R_{i}$ from other data centers which could process the task. After collecting the information, remote data centers are added to the list of available resources. They are treated like other local resources and are also considered during the local scheduling algorithm.

Each data center receiving a task wrapper message triggers an algorithm to determine if it can process the containing task. It checks if there are enough available local resources to meet the task's demands. Also the estimated processing time as well as the estimated execution cost are calculated if the task would be scheduled on this data center. Each requested data center sends back a task wrapper response $T W R_{i}$, containing the calculated information, to the requesting data center.

During resource discovery, the requesting data center awaits task wrapper response messages $T W R_{i}$ from other data centers. After collecting the remote resource information of other data centers, they are added to the local resource list. Because each task wrapper


Figure 3.6: Flowchart of the distributed scheduling approach.
response contains estimated cost and time as well as transfer time, the remote data center sending the response could be treated locally as available resource. After discovering available resources in the cloud system, the local resource scheduling algorithm is executed as described in Section 3.2. But now, tasks could also be assigned to resources which are located at remote data centers, which adds more flexibility and scalability to the local scheduling approach. The following part describes the mechanics of the resource discovery approach in detail.

### 3.3.1 Resource Discovery Approach

In a distributed system as shown in Figure 3.3, it can be very complex to discover available resources. Especially in cloud computing environments, resources are heterogenous and can have a highly dynamic availability. The overall goal is to find a resource which can process a given task while not violating the QoS requirements of meeting task deadlines. In order to meet task deadlines, the transfer time of tasks between a cloud user and a data center should be as small as possible. This could be achieved if the data center is located in the same geographical region as the user. The resource scheduling becomes more complex by adding another scheduling leveling between different data centers. The first step after a task is submitted to any data center is to find appropriate other data centers which could process the task in a more efficient way. Therefore, some kind of resource discovery is necessary. There exist several resource discovery approaches in distributed computing environments [57]. This work uses and proposes an approach which is based on agent-based discovery [58].

An agent is a software entity which has a given goal to achieve. It can react to external changes via listeners and is able to change its internal state based on different


Figure 3.7: Agent-based system model.

Table 3.4: Example of an information table of a resource manager.

| Information about $D_{n}$ | Location $Z^{D_{n}}$ | Transfer time $T T$ to $D_{n}$ |
| :---: | :---: | :---: |
| VendorX.dcAsia | 29 | 400 |
| VendorY.dcEurope | 2 | 200 |
| VendorY.dcAmerica | 10 | 120 |
| VendorZ.dcAmerica | 16 | 240 |

events [57]. The agent-based approach fits well with the concept of resource managers in this work. Every local resource manager in a data center represents an agent. Based on the approach from [58], the distributed system model assumed for this work consists of an agent hierarchy, which is organized as a Peer-to-Peer network. Therefore, the local resource manager of a data center takes over the role of an agent. If a new data center joins the system, also a new agent is created and registers with one of the existing agents to join the hierarchy. Also when a data center is no longer available, its agent notifies adjacent agents in the hierarchy and leaves the system. This hierarchy is structured as a multi-agent graph which should facilitate the discovery process. Figure 3.7 shows an example multi-agent graph based on the system model defined earlier. In the following a local resource manager refers to an agent, as defined above.

Each resource manager maintains local information which is used during the discovery process in order to determine if the data center is a possible solution candidate for processing the task. The following list describes which information is provided by the resource manager in detail.

Resource Information The resource manager always monitors its local resource pool and knows how many resources are currently being utilized and how many resources are available. Furthermore, the resource list contains information about each resource type, i.e. regarding CPU and memory capacity. If the resource manager receives a task wrapper $T W$ during the discovery process, it can easily check if it has the capabilities of processing the task.

Location Another important information is the geographical location of the resource manager, respectively the data center. In order to reduce response times, the discovery process aims at finding data centers in the same geographical location as the task.

The multi-agent graph $G$ is defined as follows:

$$
\begin{gather*}
G=(D, E) \\
D=\left\{D_{n}\right\}, n=1,2, \ldots F  \tag{3.12}\\
E=\left\{\left(D_{n}, D_{j}\right) \mid D_{n}, D_{j} \in D \cap P\left(D_{j}, D_{n}\right)\right\}
\end{gather*}
$$

A graph $G$ consists of a set of data centers $D$ and a set of edges $E$. An edge is a tuple of two data centers $D_{n}$ and $D_{j}$ whereas $P\left(D_{j}, D_{n}\right)$ denotes a direct link between data center $D_{j}$ and data center $D_{n}$. Each data center knows who its direct adjacent data centers are and can access their information. The principle of the resource discovery process is now as follows. When a task is submitted to a local resource manager, the whole process gets triggered. First of all, the local manager checks if it is already in the same region as the task submitting user. If so, it checks if enough available resources can be allocated to process the task. If both conditions are true, the task gets processed on the data center. But if any condition is false, the resource manager checks its list of adjacent data centers.

Because each resource manager maintains information about its adjacent data centers, it can check the regions of its neighbors. Table 3.4 shows an example information table of a resource manager. This table includes the name of an adjacent data center, its location and the time it takes to transfer a task to this data center. If a resource manager wants to request resource information from other data centers in the system, it creates a task wrapper $T W$ which contains the original task and forwards it to adjacent data centers. When forwarding the task wrapper to neighbors, those are preferred which do have the same region as the user. If no neighbor exists with the same region, all adjacent data centers will be selected. The following scenarios possible when a data center receives a task wrapper $T W$.
i. The discovered data center is in the same region as the user and can provide enough resources to meet the task's demands.
ii. The discovered data center is not in the same region or has not enough free resources to process the task. But the resource manager knows other data centers which are in the requested region and can forward the task wrapper $T W$ to them.
iii. The discovered data center is not in the same region or has not enough resources and does not know any adjacent data center with the requested region. But it can forward the task wrapper $T W$ to adjacent data centers.
iv. The data center does not match above defined requirements (region and resources) and does not have any adjacent data centers.

In the distributed system model, all data centers can have edges $E$ to other data centers. Each edge $\left(D_{n}, D_{j}\right)$ between data center $D_{n}$ and data center $D_{j}$ has a weight. This weight indicates the transfer time of a task between the two data centers and is assumed to be known. During the resource discovery process a task wrapper $T W$ is sent through the system from data center to data center. Each task wrapper has a reference to its current transfer time $T T$. The current transfer time is the accumulated time of all transfer times between data centers the task wrapper already has passed. It could also be referred to as path cost from the root data center to the current data center. In each


Figure 3.8: Flowchart of the discovery process.
data center the task wrappers transfer time gets updated accordingly. The total transfer time is then considered when selecting a remote data center. If a remote data center has a good location and low cost but the transfer time to this data center is too high in order to process the task within its given deadline, it would not be optimal to choose it.

Because each data center in the graph could have multiple adjacent data centers, multiple search paths could emerge. To ensure that the resource discovery process terminates and takes not too much time, a maximum depth level of forwarding task wrapper $T W$ s to adjacent data centers is defined. A concrete setting of the parameter is defined later during evaluation in Chapter 5. This depth level is defined for each search path coming from the root data center. Each time a task wrapper $T W$ is received at a new data center, a counter gets increased which represents the current number of forwards of this request. If the maximum depth level is reached in a data center it does not forward the request any more and the search path is closed. If all search paths are closed the process terminates.

Scenario ii. to iv. in the list above will either terminate the process if the maximum depth is reached, or forward the task wrapper $T W$ to other data centers. In scenario i., the discovered data center fulfills all requirements for processing the task. In this scenario the data center's resource manager estimates processing time (i.e. estimated end execution time) and processing cost. It then sends back a response with this information to the requesting data center. The discovery process only terminates if all search paths are closed and a search path is closed if either a data center has no adjacent data centers anymore or the maximum depth level is reached.

Figure 3.8 shows the whole process, triggered by a task wrapper $T W$ on a data center. First of all, the data center checks if its region matches the region of the task wrapper $T W$. If so, it then checks if enough resources are available to meet the task's demand. If this is also true, the data center begins calculating estimated cost and processing time and responds to the original requester data center. After that, or if some of the conditions were false, the task wrapper $T W$ s level counter gets updated. This counter is then compared with the maximum depth level and if it is reached the search path will be closed. If not, the resource manager checks if it knows adjacent data centers and sends the task wrapper $T W$ to them or closes the search path.

The discovery process terminates if all search paths are closed. Meanwhile, the requesting data center awaits responses from data centers which could handle the task. The next part describes how each suitable data center calculates cost and time estimates which are collected by the requesting data center in order to decide which data center should process the task.

### 3.3.2 Estimation of Processing Cost and Time

If a remote data center fulfills the location requirements and has enough resources available, its resource manager calculates an estimation of processing time and processing cost, if the task would be scheduled on this data center. For this estimation, it uses the local QoS-aware optimization model which is defined in Section 3.2. The estimated execution end time $E E T$ is simply the estimated processing time of the task on a free resource of the data center which has the capacity to fill the task's demand. The calculation is shown in Equation 3.13. $R_{j}$ refers to a free resource which can handle the task.

$$
\begin{equation*}
E E T=P T^{R_{j}}=\frac{L_{i}}{S_{j} \cdot C_{i}} \tag{3.13}
\end{equation*}
$$

Similarly, the estimated execution cost $E E C$ are calculated as shown in Equation 3.14

$$
\begin{equation*}
E E C=\left(\left(C_{\text {Cost }}^{j}\right)+\left(M_{\text {Cost }}^{j} \cdot M_{i}\right)\right) \cdot\left\lceil\frac{E E T}{\tau}\right\rceil \tag{3.14}
\end{equation*}
$$

The main difference of Equations 3.14 and 3.13 to the Equation 3.2 from the local scheduling approach is, that they are just estimations and do not reflect the real cost and execution time of the given task. They represent a snapshot of the data center's current utilization. However, these calculations are just estimations and the real values could vary because each data center could also receive other tasks at any time and therefore their local schedule could change as well as available resources. But the estimations should only support the requesting data center with an overview of the remote data center's resource and cost information which should help ensuring that the QoS requirements of the task are still satisfiable. The estimations are used to describe a remote data center as a resource with a specific execution cost and speed, just like other local resources.

### 3.3.3 Treating Remote Data Centers as Local Resources

After the discovery process for a given task, the resource manager has collected task wrapper response $T W R$ messages from remote data centers which are able to process the task. These remote data centers are added to the local list of available resources and are treated like other local resources. Because the task wrapper response from each data center contains estimated execution cost and time as well as the total transfer time $T T$ to the remote data center, the local scheduling algorithm can consider these "remote" resources when assigning tasks. The only difference to local resources is that when assigning a task to a remote resource, the transfer time to that remote resource must also be considered in order to meet the deadline constraint of the task. After adding all remote data centers to the resource list, the local resource manager starts the local scheduling algorithm as described in Section 3.2 and incoming tasks could either be assigned to local or remote resources.

### 3.3.4 Resource Manager

The resource manager on each data center plays a central role and has certain responsibilities regarding the local and global resource scheduling. Each resource manager can act as a requester data center and as a "responder" data center. All presented concepts above are combined through the resource manager and therefore this section lists all important duties of the resource manager and describes them in detail.

Receive tasks First of all, the resource manager is responsible for receiving tasks submitted by users. It must decide if the task should be scheduled locally or if it should forward the task to a remote data center which could fulfill all QoS requirements.

Local scheduling One of the main tasks of the resource manager is of course the local scheduling. It is responsible for executing the local PSO algorithms in order to generate an optimal schedule based on the QoS model.

Handle task wrapper messages Resource managers receive not only submitted tasks by users but also task wrapper $T W$ messages from other data centers in the system. When receiving a task wrapper, the resource manager has to check if it is able to satisfy the task's demand with respect to location and resource capacity. If a task wrapper $T W$ could be fulfilled, it is also responsible for sending a response message back to the request data center. Additionally, the task request must be forwarded to other known resource managers. The whole process for handling task wrapper $T W$ messages is shown in Figure 3.8.

Estimate task-processing properties If a task wrapper $T W$ was received and could be handled by the local resources, the resource manager has to estimate processing cost and processing time as if the task would be scheduled on the data center. This estimations are sent within a respond message back to the request data center.

Organization with other resource managers In order to forward incoming task wrapper $T W$ messages, each resource manager in the system knows the resource managers from its adjacent data centers. Beside that, the transfer time to an adjacent resource manager is also known as well as its location. This information is stored in an internal table as shown in Table 3.4. If a new data center joins the system, its resource manager informs other resource managers in the system as well as if a data center disappears. The internal table gets updated accordingly each time a data center joins or leaves the system.

If a task is submitted to a data center in the cloud system, there are two phases which it must pass. First of all, the resource discovery is triggered by the local resource manager. This should ensure that the task gets forwarded to a data center which i) is in the same location as the submitting user and ii) has enough free resources to process the task within a satisfiable QoS level. The resource discovery layer adds also more scalability and flexibility to the whole system because the execution of a task depends not on a single data center anymore. The second phase is the local scheduling on a concrete data center. The local scheduler mainly aims at minimizing execution cost while guaranteeing that predefined task deadlines are satisfied.

The combination of global and local scheduling should not only improve system efficiency and local resource utilization but also reduce the average response times between cloud providers and consumers while other QoS requirements like execution cost and task deadlines are still satisfied. The next chapter provides a concrete implementation of the local scheduling approach as well as of the distributed resource discovery approach and the resource manager in order to simulate the whole approach under realistic conditions.

## CHAPTER

## Implementation

In this chapter a concrete implementation of the presented concepts from Chapter 3 is described. Moreover, this implementation includes a local scheduling algorithm based on the PSO technique and a resource discovery approach, which relies on event-based messaging. The implementation is done in CloudSim 4.0, a framework for modeling and simulation of cloud computing infrastructures and services written in the programming language JAVA. Before discussing the implementation details, a brief introduction to CloudSim's architecture and its basic concepts is given. Then, the implementations of the local scheduling and the global resource discovery are presented and their integration into the CloudSim framework is discussed.


Figure 4.1: Layered architecture of CloudSim [59].

### 4.1 CloudSim 4.0

Figure 4.1 shows the architecture of CloudSim, which is divided into multiple layers. Basically, there are two simulation layers which could be extended for providing specific implementations with custom resource allocation strategies. The first one is the CloudSim layer, which supports the modeling of issues such as provisioning physical resources to virtual machines [59]. This layer is useful for cloud providers who want to test the efficiency of different resource provisioning strategies and will not be targeted in this work. The second layer is the User code layer, which exposes basic entities for virtual machines, cloud users and their applications. Following activities can be performed within this layer [59:

- Generation of distributed workload requests with custom configurations
- Modeling of cloud availability scenarios
- Implementation of custom task provisioning (scheduling) techniques

Because of its capabilities, we extended the entities of the User code layer for providing implementations of the resource scheduling and resource discovery techniques presented in Chapter 3. A task, submitted by a cloud user is represented by the Cloudlet entity in CloudSim. The Cloudlet encapsulates information about length, status, start and finish time as well as the ID of the resource (virtual machine) it is assigned to. A cloud resource is represented by an entity called $V m$, which encapsulates information about memory, number of CPUs and the processing speed. The DataCenterBroker models a broker which is responsible for mediating negotiations driven by QoS requirements between cloud users and cloud providers [59]. The broker takes a list of tasks which should be scheduled from the user and a list of available virtual machines. The broker is also responsible for resource scheduling policies and could be extended for implementing custom scheduling strategies.

Another important feature of CloudSim is its capability of modeling realistic networking topologies and models. Different cloud entities like users, resources and data centers could be connected with each other to different network topologies where the latency of messages between two entities could be modeled. The inter-networking between these entities is based on a conceptual networking abstraction (i.e. in the simulation framework exist no network entities like routers and switches) [59. We use the networking capabilities in order to simulate a cloud system consisting multiple data centers at different locations as shown in the motivating scenario in Section 3.1.

The next two parts describe first, how the proposed PSO-approach for local resource scheduling is implemented using the above presented entities from CloudSim and second, how the global resource discovery is integrated using the networking event-based system of CloudSim.


Figure 4.2: Architecture of the implementation.

### 4.2 Local Resource Scheduling

In order to implement a custom resource scheduling strategy, we extend the DataCenterBroker entity provided by CloudSim and call this extension ResourceManager. This class should be able to perform all operations as described in Section 3.3.4. Figure 4.2 shows the complete implementation architecture for the proposed approach, where the entities with bold names are entities provided by the CloudSim framework. The Resource Manager contains a service class called PSOProcess, which performs the actual PSO algorithm as described in Section 3.2. The Particle class is used to encapsulate information for each particle in the swarm like position, $p$ Best, $p$ BestLocation and velocity. The details of the PSOProcess and its particles are described later in this section.

The Cloudlet entity provided by CloudSim has no capabilities to model QoS requirements of the cloud user by default. In order to define the QoS requirements necessary for the proposed approach, we extend the Cloudlet class by a custom-defined class called Task. A task contains a reference to exactly one Cloudlet object and additionally has fields which declare the task's deadline and its budget. Also, in order to define custom CPU and memory cost, we extended the Vm entity by a class called Resource which provides the additional fields.

Each Resource Manager contains an entity called Schedule, which encapsulates information about the current scheduling state. A Schedule consists of several Mappings, where each mapping contains a Task and Resource which should process that Task. A

Mapping also stores information about the execution start and the execution end of the task. With this information given, each mapping could calculate the execution cost as well as the deadline and budget violation of the related task. A Schedule could then aggregate the individual values provided by its Mappings and calculate total execution cost and total constraint violation of all Mappings in the Schedule. A Schedule is generated after each iteration from the PSOProcess according to Algorithm 3.2. The PSOProcess defines one public method called execute() which returns a schedule object. The returned schedule is the optimal schedule with minimal total execution cost under the given deadline and budget constraints for the submitted Tasks and the given set of Resources. The execute() method runs the following steps in order to find an optimal Schedule:

Initialize swarm Based on the given set of tasks and resources, a swarm of particle objects is initialized. The size of the swarm reflects the number of given tasks. Each particle is initialized with a random position in a specific range. If a particle's position changes during the process and exceeds the upper or lower limit, it is automatically set to these limits respectively. The fields $p$ BestLocation and $p$ Best of each particle are also initialized based on the random start positions. pBestLocation contains the best found position so far by the particle, where pBest stores the according total execution cost of the generated Schedule based on the position in pBestLocation.

Updated positions Based on Equations 3.7 and 3.8 , the velocity and positions is updated and stored for each particle. As described above, the position can not exceed the upper and lower limit. The upper limit is equal to the amount of given Resources, because the particle positions should indicate a resource by its index.

Calculate schedule and update pBest After updating positions, two Schedules are generated. One Schedule is generated out of the current particle positions and the second Schedule is generated out of the pBestLocation positions. These two Schedules are now compared based on the constraint-handling strategy proposed in Section 3.2. If the Schedule generated from the updated positions is better than the current best Schedule, then the $p$ Best for each particle is set to the total execution cost of the new Schedule and pBestLocation is set to the current position of each particle.

Update gBest After updating all $p B e s t$ values, the $g B e s t$ value is updated by the best solution found so far.

Return optimal schedule The previous three steps are executed in a loop until a maximum number of iterations is reached. The iteration number will be defined during the evaluation in Chapter 5. After the iteration terminates, a schedule is generated out of each particle's pBestLocation position and gets returned to the Resource Manager.

The Resource Manager has a public method called runScheduling() which starts the PSOProcess. After the process is finished, the Resource Manager has a Schedule which contains the Mappings from all Tasks to the available Resources. It iterates over each Mapping and assigns each Task to the corresponding Resource in the Mapping according to the execution start times. This is necessary because the mapping just contains the two objects, but the simulation engine needs to know which Resource should process which Task at a specific time. After assigning all Tasks, the Resource Manager submits the list to the data center and the actual simulation starts.

### 4.3 Global Resource Discovery

For the global resource discovery algorithm, as described in Section 3.3.1, we extend the resource manager with more functionality. The following list describes the methods used and implemented by the resource manager in order to perform the proposed discovery approach:
startResourceDiscovery(task) This method starts the discovery process. The resource manager iterates over a internal hash map which stores adjacent resource managers along with the transfer cost to them. This method gets invoked for each local task which has a different region than the current resource manager. A new task wrapper is created for each adjacent manager and initialized with the maximum search depth level as well as the requesting manager. Before the task wrapper is sent, also the transfer time to the adjacent resource manager is already added. To send the task wrapper to another resource manager, the method onTaskWrapperReceive() of that manager is invoked with the task wrapper as parameter.
onTaskWrapperReceive(taskWrapper) This method gets invoked each time a task wrapper is received from another resource manager. First, it increments the search depth of the task wrapper by one and checks then if the region of the task wrapper is the same as the own region. If so, it creates a task wrapper response and calls the method getAppropriateResource() in order to get an available resource which could handle the task. It then creates a new remote resource object which extends a resource and adds a field which holds the transfer cost to the current resource manager. The transfer cost is later considered during the schedule generation and added as delay to the execution start time of the task. The remote resource object is added to the response message which is then sent back to the requesting resource manager by invoking its onTaskWrapperResponseReceive() method. Finally it checks if the maximum search depth level for the task wrapper is reached. If not, it creates a new task wrapper out of the current one and sends it to all adjacent managers. But an adjacent resource manager could have already received the same task wrapper before. Therefore, the task wrapper itself has an internal list which contains all resource managers which received the task wrapper so far. The
task wrapper is then only forwarded to a manager if it is not already in the task wrapper's list.
onTaskWrapperResponseReceive(taskWrapperResponse) This method is called each time a resource manager receives a task wrapper response message from another resource manager. The response message contains a remote resource object which was selected by a remote resource manager as reaction to a task wrapper request message. The remote resource is then added to the internal list of available resources and will be considered during the local scheduling process.
getAppropriateResource(task) Each time a resource manager needs to find an available resource which could meet the demands of a specific task, this method gets called in order to provide that resource.

The global scheduling process is shown in Figure 4.3 and now looks as follows. First, there is an iteration over each submitted task. Each task's location is checked and if it does not match the location of the resource manager, a resource discovery process is started for this task by calling the startResourceDiscovery() method with the task as parameter. After the resource discovery, the resource manager may have additional remote resources added to its list of available resources. With these remote resources and its own resources, the local resource scheduling process is started by calling the runScheduling() method which assigns resources to tasks. The tasks could now be assigned to either local resources or remote resources from other resource managers.


Figure 4.3: Global scheduling process.

## Evaluation

In this chapter the evaluation of the proposed approaches from Chapter 3 is presented. For evaluating the approaches, we use the CloudSim implementation described in Chapter 4. The first section describes the experimental setup and how necessary scheduling parameters are defined, as well as how realistic datasets used for the simulation are generated. After that, different simulation scenarios are presented which are each evaluated and compared with each other. There are three scenarios which are used for evaluation: i) A centralized scenario, where only a single data center exists and all tasks are scheduled in this data center. ii) A distributed scenario where multiple data centers exists at different locations and some of them are connected with each other. Cloud consumer tasks are distributed among the data centers and could be scheduled on any data center. iii) A first fit scenario, which has the same setup as the distributed scenario, but during resource discovery the first matching data center will terminate the process and other data centers in the system will not be considered.

Different metrics like for example total execution cost, deadline violation rate and task completion rate will be measured for each scenario and the results are then compared with each other. Based on the results, an evaluation will be done on how the distributed approach performs compared to a centralized one in terms of user QoS.

### 5.1 Experimental Setup

Before running the simulation using the different scenarios, test data must be generated and basic parameters need to be defined in order to run the PSO scheduling algorithm. The generated data includes workloads (i.e. tasks from cloud consumer) and resources (i.e. virtual machines). To simulate a realistic and complex environment, all data is generated randomly. This includes several VM and task characteristics. Table 5.1 shows the different characteristics of tasks and resources and how they are generated.

Table 5.1: Task and resource generation settings

| Characteristic | Value |
| :---: | :---: |
| Task location $Z^{T_{i}}$ | $[1,3]$ |
| Task length $L_{i}$ | $[1,10]$ |
| Task budget $B_{i}$ | $\operatorname{Normal}\left(L_{i}, 2\right)$ |
| Processing speed $S_{j}$ | $[1,10]$ |
| CPU Cost $C_{\text {Cost }}^{j}$ | $\operatorname{Normal}\left(S_{j}, 2\right)$ |
| Memory Cost $M_{\text {Cost }}^{j}$ | 0.05 |

Table 5.2: Cloud Environments

| Scale | Configuration |
| :---: | :---: |
| Small | 50 tasks, 5 resources |
| Middle | 200 tasks, 5 resources |
| Large | 600 tasks, 5 resources |

The location of a task is randomly generated within a range from 1 to 3 . In order to simulate realistic values, the task lengths are randomly chosen in a range between 1 and 10 . Task budgets usually depend on the task length, therefore they are randomly generated by a normal distribution with a mean influenced by the task length. The actual calculation of the means is shown in Table 5.1. The processing speed of a resource is randomly chosen in a range of 1 to 10 . Because the cost of a resource usually depends on its performance, the CPU cost is randomly generated by a normal distribution with a mean set to the processing capacity $S_{j}$. The memory cost of a resource are fixed to 0.05 , which is a typical price set by real cloud providers (e.g. Amazon Web Services).

The evaluation is done using three different scales of cloud environments, a small, a middle and a large scale environment. The actual settings of the amount of tasks and resources used for each environment is shown in Table 5.2. Each scenario is simulated in the three different cloud environments in order to measure the behavior of the proposed technique for changing circumstances. Finally, 5.3 shows the parameter setting of the local PSO scheduling algorithm. These parameters were chosen after several experiments with different settings. They lead to a fast convergence of the PSO algorithm in most cases.

### 5.2 Simulation Scenarios

In this section, three scenarios used to evaluate the proposed approach are presented and described in detail. We execute each simulation in 30 independent runs in order to get robust test results. Each scenario will be simulated with all three differently scaled cloud environments presented in Table 5.2. The following list describes each scenario and the actual cloud system setup used.

Table 5.3: PSO parameter settings

| Parameter | Value |
| :---: | :---: |
| Generations | 1000 |
| $\omega$ | 0.5 |
| $\rho$ | 0.8 |
| $c_{1}, c_{2}$ | 2.0 |
| $r_{1}, r_{2}$ | $[-1,1]$ |



Figure 5.1: Setup of the simulation scenario.

Centralized Scenario Most existing solutions in real cloud systems have a centralized architecture. Therefore, a single data center is used to schedule all tasks in the first scenario. The resource scheduling algorithm has only access to local resources. This scenario is also called centralized scenario, because the tasks are scheduled on one central point. For scheduling, only the proposed PSO algorithm from Chapter 3 is used.

Distributed Scenario This scenario is conducted for usage with the proposed global resource discovery approach from Chapter 3. Figure 5.1 shows the setup of this scenario. There are multiple data centers in different geographical regions. Some of the data centers are connected with each other and the transfer cost between to data centers is known. In Figure 5.1, the transfer cost is denoted as the label of an edge between to data centers. The cost were chosen in order to provide a setup close to real world, with fast and slow connections between different data centers. When using multiple data centers, tasks submitted by a cloud user could not only be scheduled on the data center to which he submitted but also on other data centers in the system which can provide suitable resources meeting the user's QoS requirements. This should not only ensure that the QoS requirements are
satisfied but also increase the overall system efficiency as well as the scalability and flexibility. In order to achieve this, both the local PSO scheduling algorithm and the global resource discovery approach are utilized.

First Fit Scenario The final scenario uses the same setup as the distributed one and also both the local and the global scheduling approaches are applied. The main difference in this scenario is that during the resource discovery the first resource is returned which is able to process the task. This means the discovery process terminates if one resource is found which could handle the task, even if there are other resources available in the system, which may be better suited. The results gained from simulating this scenario will be used to compare the performance of the resource discovery approach itself and, if the approach is applied, better results in terms of execution cost and deadline violation could be gained.

Each data center in the setup has the exact same amount of resources as defined in Table 5.2. To keep the simulation simple, all resources within a data center belong to a single host. We assume that each data center host has enough capabilities to host the randomly generated resources.

### 5.3 Results and Comparison

This section analyzes the simulation results of the different scenarios and compares them with each other. The results are compared using four different metrics observed from the simulation runs: i) execution cost, ii) deadline violation, iii) task completion and iv) makespan. The first two, execution cost and deadline violation are the most interesting one with regards to the user QoS requirements defined in the optimization model. The task completion measures how many tasks were actually processed, because if the execution costs exceed the user-defined budget the task will not be processed. With the makespan we measure how fast the submitted tasks are processed. These metrics are not only compared among the different scenarios but also among the different cloud environment scales (small, middle and large) used in each scenario. In the following the results for each different metric will be compared and discussed and in the end the overall outcome of this experiment will be summarized. A complete list of the numerical simulation results for each scenario and scale can be found in Appendix A.

### 5.3.1 Statistical Analysis

In order to provide solid statements about the observed simulation results, they must be analyzed first. Therefore for each metric boxplots are provided in the subsequent chapters. Additionally all metrics are tested using the Friedman-Test in order to determine if the results observed from the 30 independent simulation runs are different. The simulation results were tested with the Sharpio-Wilk-Test to check wether the results are normally distributed and additionally for each metric a normal probability plot was

Table 5.4: Friedman-Test results for the Centralized Scenario

| Scale | Execution Cost | Deadline Vio. Rate | Task Compl. Rate | Makespan |
| :--- | :---: | :---: | :---: | :---: |
| Small | 0.11 | 0.5 | 0.17 | 0.26 |
| Middle | 0.97 | 0.78 | 0.96 | 0.49 |
| Large | 0.28 | 0.6 | 0.25 | 0.68 |

Table 5.5: Friedman-Test results for the Distributed Scenario

| Scale | Execution Cost | Deadline Vio. Rate | Task Compl. Rate | Makespan |
| :--- | :---: | :---: | :---: | :---: |
| Small | 0.3 | 0.99 | 0.27 | 0.85 |
| Middle | 0.69 | 0.81 | 0.8 | 0.58 |
| Large | 0.57 | 0.94 | 0.5 | 0.86 |

Table 5.6: Friedman-Test results for the First Fit Scenario

| Scale | Execution Cost | Deadline Vio. Rate | Task Compl. Rate | Makespan |
| :--- | :---: | :---: | :---: | :---: |
| Small | 0.35 | 0.003 | 0.38 | 0.01 |
| Middle | 0.2 | 0.14 | 0.12 | 0.01 |
| Large | 0.007 | 0.08 | 0.005 | 0.32 |

created. It could be observed that for both methods each metric in the simulation results is not normally distributed. Therefore the Friedman-Test is applicable for testing differences in the observations.

The null hypothesis of the Friedman-Test is, that there is no difference in a treatment across multiple test attempts. In the context of the simulation results a treatment is the value of a metric (e.g. execution cost). A test attempt is one simulation run and the data is blocked by the different deadlines. If the p-value is less than 0.05 the null hypothesis will be rejected. This means at least one value of a test attempt is significantly different to a value from another test attempt. The Tables $5.4,5.5$ and 5.6 show the p-values of the Friedman-Test for every metric at the three different scales and scenarios.

For both the centralized and distributed scenario the p-values for all metrics at every scale are greater than 0.05 and therefore we can assume that results gained from the multiple simulation runs do not differ. Only in the first fit scenario some metrics significantly differ from each other for one or many simulation runs. This is especially the case on a large scale. One reason might be that during the resource discovery phase every time the first available resource is returned and not a resource which may be better. Therefore sometimes the resource could be good and sometimes a resource is returned which does not fulfill the demands perfectly. There is no check for cost and performance and the resource return has no meaning to the task and they could of course significantly differ at each simulation run.

### 5.3.2 Evaluation of Execution Cost

The total execution cost of the three scenarios for the different environment scales are shown in Figure 5.2. Boxplots for all scenarios and scales are shown in Figure 5.3 As described above, all results are the average of 30 independent simulation runs with tasks and resources generated randomly for each run. Additionally the charts show the different metrics for different deadlines, starting at very tight deadlines and going to loose deadlines in the end. At every scale the execution cost are higher for very tight deadlines and are then converging to a stable value if the deadlines loosen. This is because at tight deadlines, tasks require better and more performant resources for their completion within the deadlines. Therefore the corresponding costs will be higher because faster resources are more expensive.

Also, at every scale and for all different deadlines, the execution costs of the distributed and first fit scenarios are lower than the cost of the centralized scenario. This difference increases with the scale of tasks to schedule. The execution cost of the distributed and first fit scenarios are nearly the same for loose deadlines, but at very tight deadlines the distributed approach has slightly lower costs. Especially in the large scale the cost at tight deadlines are much lower for the distributed approach. In the distributed and the first fit scenario, the resource managers have access to more resources than in the centralized scenario. Because of that, they may find performant resources with lower cost than a centralized resource manager which is restricted to local resources only. Therefore the cost for tight deadlines is lower in the distributed and the first fit scenario. Moreover, the resource discovery approach in the distributed scenario may find better and more resources than the approach in the first fit scenario, which only returns the first available resource. This reasons the slightly better results of the distributed approach compared to the first fit one.

To sum up, the execution cost are lower for distributed approaches which consider resources from other data centers and especially for tight deadlines the approach proposed in this work generates the best results.

### 5.3.3 Evaluation of Deadline Violation

Figure 5.4 shows the deadline violation rates for the different scales with different deadlines. Boxplots for all scenarios and scales are shown in Figure 5.5. The first thing to notice is that the violation rate decreases with loosening of deadlines. Obviously the deadline violation rates in all scenarios are lower for fewer tasks than for many tasks, because fewer tasks have more resources to be scheduled on. In the small scale the deadline violation rate is nearly the same in all scenarios, this means the amount of local available resources in a data center is large enough to satisfy the demands of every task and the distributed mechanism adds no advantage. This changes if the number of tasks increases. For the middle scale environment the violation rates in the first fit scenario are slightly better than the centralized one and even better in the distributed scenario, especially for tight deadlines. This is because for many tasks, the local available




Figure 5.2: Total Execution Cost with different deadlines and scales.


Figure 5.3: Boxplots for the execution cost in different scenarios and scales.




Figure 5.4: Deadline Violation Rate with different deadlines and scales.
resources within a data center are not sufficient any more and many tasks have to wait for resources. Through the resource discovery approaches, more resources are available for processing tasks and thus fulfilling the deadline requirements. This is especially the case when the resource discovery approach considers multiple data centers and not only the first available one as in the first fit scenario.

The proposed, distributed approach outperforms the classic centralized approach in terms of deadline violation only in large scale environments. In scenarios with little workloads, the deadlines could also be met when only considering local resources, but if the number of resources increases, the local resources are not enough any more to fulfill the deadline requirements of each task. The first fit approach enables the utilization of more resources and the distributed approach utilizes even more remote resources which reduces the overall deadline violation rate.

### 5.3.4 Evaluation of Task Completion

The task completion rate reflects the number of submitted tasks which were successfully scheduled and is shown for the different scales in Figure 5.6. Boxplots for all scenarios and scales are shown in Figure 5.7. In the context of our experiments, a task will be scheduled if its execution costs do not exceed its budget assigned by the cloud user. The task completion slightly decreases in all three scenarios with increasing tasks. In the scenarios which use a resource discovery approach the task completion rate stays nearly around $90 \%$ for loose deadlines. In the centralized scenario, the task completion declines rapidly if the number of tasks increases. For tight deadlines, the distributed approach has the highest task completion rates, especially in middle and large scale environments. The task completion directly depends on the total execution cost as seen in Section 5.3 .2 . If the total cost are low, the task completion is higher because the user-defined budgets for each task could be satisfied. For tight deadlines, this is perfectly consistent with the results for the execution cost as shown in Figure 5.2 .

### 5.3.5 Evaluation of Makespan

The makespan is the total time which elapses from the beginning (i.e. submission of tasks) to the end (i.e. all tasks processed). The average result for the different scales is shown in Figure 5.8. Boxplots for all scenarios and scales are shown in Figure 5.9. The makespan in each scenario increases with increasing amounts of tasks to schedule, but according to the different deadlines the makespan behaves differently in each scenario for each scale. At a small scale the makespan in the centralized scenario stays nearly constant for every deadline. In the two scenarios which use distributed resource discovery approaches, the makespan rapidly increases with looser deadlines. This could have different reasons. First, if the task deadlines loosen, resources with less performance are selected to schedule the tasks which decreases the overall performance on one hand but also reduces execution cost on the other hand. The reason why the makespan increases rapidly in the distributed scenarios for a small scale is that for a small amount of tasks


Figure 5.5: Boxplots for the Deadline Violation Rate in different scenarios and scales.


Task Completion Rate for 200 Tasks


Task Completion Rate for 600 Tasks


Figure 5.6: Task Completion Rate with different deadlines and scales.


Figure 5.7: Boxplots for the Task Completion Rate in different scenarios and scales.



Makespan for 600 Tasks


Figure 5.8: Makespan with different deadlines and scales.
the locally available resources are capable of scheduling all tasks without letting tasks wait on processing. In the distributed scenarios remote resources may be selected for processing tasks even if the local resource manager could handle all tasks and because of the transfer times to this remote resources the makespan increases. For the middle and large scale, the makespan of the centralized scenario increases the same as in the other two scenarios, because now locally available resources are not enough any more to process all tasks at once and some tasks have to wait which increases the overall execution time. Using the distributed approaches does not increase makespans compared to a centralized approach but heavily reduces cost and deadline violation rates, especially for the middle and large scale.

### 5.4 Summary of the Observed Results

As shown in the results, distributed resource scheduling approaches which consider resources from different data centers achieve significantly lower execution cost compared to centralized approaches. This is mainly because of the larger amount of resources available, where the cheapest could be selected in order to process the incoming workloads. This advantage gets even bigger for very tight deadlines and large scale environments. In terms of deadline violation, the two distributed approaches outperform the centralized one in the middle and the large scale scenarios. At a small scale, local resources are enough to meet all deadlines and therefore no advantages are gained when using a distributed scheduling approach. But significant differences could be observed in a large scale where the deadline violation rate in the distributed scenario is $30 \%$ to $40 \%$ lower compared to the rate in the centralized scenario.

At every scale, task completion rates increase with looser deadlines and also at every scale, the distributed and first fit approach achieve better completion rates than the centralized approach. There is a significant difference of completion rates between the three scenarios for the large scale scenario and at very tight deadlines. The distributed approach can achieve the best results. These results directly correlate with the results for the execution costs. If the total execution cost are high, fewer tasks could be processed within their budget and task completion rate sinks. The completion rate increases if the total execution cost are low and more tasks could be processed within their budget. When comparing makespans, it can be observed that the makespan for a small scale environment is smaller at all deadlines in the centralized approach. In the first fit and distributed scenarios, makespans are very high at loose deadlines for a small scale. The reason why the centralized approach has a better performance is that all resources used for processing tasks are locally available and no transfer time to remote resources is added. In larger scales, this disadvantage becomes less significant because there are too many tasks for a single data center and therefore many tasks have to wait to be processed which increases the makespan in the centralized scenario.

The proposed approach of this work, which uses a distributed resource discovery approach outperforms a centralized approach significantly in middle and large scale


Figure 5.9: Boxplots for the makespan in different scenarios and scales.
environments, especially in terms of execution costs and deadline violation rates. Also at very tight task deadlines the distributed approach achieves reasonable results for the total execution cost and therefore also for task completion. In small scales environments the approach performs quite worse in terms of makespan compared to a centralized approach, mainly because of the transfer times to the remote resources. But when considering user QoS like execution cost and deadlines, the system makespan does not matter much if the individual requirements are satisfied.

### 5.5 Limitations and Future Work

This section outlines known limitations of the proposed approach and discusses issues which could be addressed in future work. First of all, a serious limitation is that the proposed approach is designed for scheduling only single task requests. This is in reality not often the case and most times a workflow consisting of multiple single tasks is submitted by a cloud user in order to be scheduled. Centralized approaches targeting workflow scheduling already exist and were implemented successfully [10, 11, 12, 13]. A further research direction would be the distributed scheduling of task workflows. Also, the optimization model of this work considered only task deadlines as QoS constraints. This could be extended to multiple QoS constraints for distributed resource scheduling methods.

The resource discovery approach works on a hierarchy of agents which are represented by the resource managers of the data centers. Usually a resource manager notifies other resource managers in the system if it joins or leaves the system. This is necessary for keeping the internal table with information of adjacent resource managers updated for each manager. But if a resource manager crashes, it is not able to notify its adjacent managers any more and therefore their tables never get updated. This could lead to less system performance because other resource managers may try to connect to not available resource managers during the resource discovery process. To avoid this, pings could be used which periodically check the health of a resource manager. In the proposed resource discovery approach we also assume transfer cost to be known between two different data centers. In a realistic environment, transfer cost may not be known in advance and could even vary for different tasks. This could be extended by analyzing for example historical values for transfer cost in order to create a more realistic environment.

## CHAPTER

## Conclusion

This work proposes an approach which utilizes distributed mechanisms for scheduling tasks submitted by cloud users to cloud resources. Compared to centralized approaches, cloud resources are not only considered from a single data center but from multiple data centers at different locations. The optimization objective of the scheduling problem is the minimization of the total task execution cost. This is constrained by individual task deadlines and budgets defined by the cloud user. Our approach also considers the geographical locations of cloud users (and their tasks) and data centers. The location is used in the resource discovery algorithm in order to find resources in the same location as the user. Our approach is divided into two phases: (i) the local scheduling phase and (ii) the distributed resource discovery phase. In the local scheduling phase, tasks are mapped to available resources and this is done within a single data center. The local scheduling is done using a particle swarm optimization algorithm.

During the resource discovery phase, a resource manager requests multiple adjacent data centers for scheduling a specific task. Data centers which are in the same region as the task are preferred. Some data centers may be able to schedule the task and respond to the requesting data center with a free resource. This resource gets added to the resource list of the manager and is available for processing tasks during the scheduling phase. Using this approach, a data center is not restricted to local resources any more and could assign tasks to remote resources which may be cheaper than local resources and reduce the total execution cost. In the following part we conclude this thesis by answering the research questions defined in Chapter 2 .

## i "How can local and global requirements be combined during QoS-aware cloud resource collection in a distributed system?"

The optimization objective of our approach is the minimization of total execution cost. This objective is constrained by user QoS requirements like task deadlines and task
budget. Both local and global requirements are to find resources which do not violate the constraints for a task which is processed on that resource. Therefore, only remote resources which are capable of processing a given task without violating any constraints are returned to a requesting resource manager. This is ensured during the resource discovery phase.
ii "How can QoS-aware cloud resource scheduling be realized in a distributed way?"

As described above, a resource manager can trigger a resource discovery mechanism where adjacent remote data centers are requested to process a given task. A task wrapper message is sent through the system which contains information about the task to be processed. If a data center is able to process the task it sends back a task wrapper response. Using this approach a resource manager has not only access to local resources but also to remote resources during resources scheduling.
iii "How does distributed QoS-aware cloud resource scheduling perform compared to centralized approaches?"

In terms of execution cost, a distributed approach outperforms centralized ones for every cloud environment scale. Deadline violation rates are much smaller for middle and large scale environments. For small scales the locally available resources are sufficient in order to process every task within its deadline. Also in terms of task completion, which is related to the execution cost, the distributed approach achieves better performance. Generally could be observed that for tight deadlines and many tasks, a distributed approach performs better in terms of execution cost and deadline violations.

## List of Figures

2.1 Layers of a cloud environment, based on 21. ..... 7
2.2 Resource mapping in the cloud, based on [24] ..... 9
2.3 Architecture of an autonomic system (MAPE loop), based on [18, 29]. ..... 9
2.4 Resource scheduling problem in the cloud, based on 9 ] ..... 11
2.5 Feasible region of simple linear program with two variables. ..... 13
2.6 A general EC framework, based on [39] ..... 14
2.7 Operation of the Genetic Algorithm, based on [42]. ..... 16
2.8 Possible construction graph for a 4-city TSP ..... 17
2.9 Feedback control loop architecture, based on [16] ..... 19
2.10 Flowchart of the DOGA approach, based on 10 ..... 21
2.11 Framework model of the PBACO approach, based on [53]. ..... 22
2.12 Example workflow in a cloud, based on [11]. ..... 23
2.13 Architecture of Cloud auto-scaling, based on 13 ..... 25
3.1 Example cloud resource scheduling scenario. ..... 30
3.2 Local system model of a data center. ..... 33
3.3 Global system model. ..... 34
3.4 Example of a generated schedule for incoming tasks. ..... 36
3.5 Flowchart of the local scheduling approach. ..... 42
3.6 Flowchart of the distributed scheduling approach. ..... 43
3.7 Agent-based system model. ..... 44
3.8 Flowchart of the discovery process. ..... 47
4.1 Layered architecture of CloudSim 59 . ..... 51
4.2 Architecture of the implementation. ..... 53
4.3 Global scheduling process. ..... 56
5.1 Setup of the simulation scenario. ..... 59
5.2 Total Execution Cost with different deadlines and scales. ..... 63
5.3 Boxplots for the execution cost in different scenarios and scales. ..... 64
5.4 Deadline Violation Rate with different deadlines and scales. ..... 65
5.5 Boxplots for the Deadline Violation Rate in different scenarios and scales. ..... 67
5.6 Task Completion Rate with different deadlines and scales. ..... 68
5.7 Boxplots for the Task Completion Rate in different scenarios and scales. ..... 69
5.8 Makespan with different deadlines and scales. ..... 70
5.9 Boxplots for the makespan in different scenarios and scales. ..... 72

## List of Tables

2.1 Selection of different cloud resource scheduling approaches ..... 20
2.2 Example encoding of a particle in RNPSO ..... 23
3.1 Notation of variables and definitions ..... 32
3.2 Example encoding of particles. ..... 39
3.3 Task to resource mapping. ..... 39
3.4 Example of an information table of a resource manager. ..... 45
5.1 Task and resource generation settings ..... 58
5.2 Cloud Environments ..... 58
5.3 PSO parameter settings ..... 59
5.4 Friedman-Test results for the Centralized Scenario ..... 61
5.5 Friedman-Test results for the Distributed Scenario ..... 61
5.6 Friedman-Test results for the First Fit Scenario ..... 61
1 Simulation Results Centralized Scenario for 50 tasks. ..... 87
2 Simulation Results Distributed Scenario for 50 tasks. ..... 99
3 Simulation Results First Fit Scenario for 50 tasks. ..... 111
4 Simulation Results Centralized Scenario for 200 tasks. ..... 123
5 Simulation Results Distributed Scenario for 200 tasks. ..... 135
6 Simulation Results First Fit Scenario for 200 tasks. ..... 148
7 Simulation Results Centralized Scenario for 600 tasks. ..... 160
8 Simulation Results Distributed Scenario for 600 tasks. ..... 172
$9 \quad$ Simulation Results First Fit Scenario for 600 tasks. ..... 184

## List of Algorithms

2.1 Genetic Algorithm Metaheuristic, based on 43] ..... 15
2.2 Ant Colony Optimization Metaheuristic, based on [45] ..... 16
2.3 PSO update process, based on [50] ..... 18
3.1 Process of a PSO ..... 38
3.2 Schedule Generation ..... 41

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Table 1: Simulation Results Centralized Scenario for 50 tasks.

| Dl. | Simulation | Exe. Cost | Dl. Vio. | Budget Vio. | Tasks fin. | Tasks fail. | Tasks Compl. | Resp. Times | Makespan |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 5,00 | , 00 | 101,66 | , 84 | , 12 | 44,00 | 6,00 | , 88 | 1,15 | 32,25 |
| 5,00 | 1,00 | 129,33 | , 70 | , 28 | 36,00 | 14,00 | , 72 | , 97 | 20,20 |
| 5,00 | 2,00 | 159,57 | , 82 | , 44 | 28,00 | 22,00 | , 56 | 1,24 | 40,67 |
| 5,00 | 3,00 | 128,25 | , 74 | , 26 | 37,00 | 13,00 | , 74 | , 83 | 22,75 |
| 5,00 | 4,00 | 99,06 | , 70 | , 22 | 39,00 | 11,00 | , 78 | , 94 | 16,83 |
| 5,00 | 5,00 | 28,76 | , 86 | , 08 | 46,00 | 4,00 | , 92 | 1,28 | 36,25 |
| 5,00 | 6,00 | 136,36 | , 80 | , 26 | 37,00 | 13,00 | , 74 | 1,62 | 52,50 |
| 5,00 | 7,00 | 189,72 | , 78 | , 42 | 29,00 | 21,00 | , 58 | 1,10 | 32,25 |
| 5,00 | 8,00 | 32,81 | , 86 | , 10 | 45,00 | 5,00 | , 90 | , 51 | 26,89 |
| 5,00 | 9,00 | 150,41 | , 66 | , 28 | 36,00 | 14,00 | , 72 | , 59 | 25,62 |
| 5,00 | 10,00 | 47,87 | , 78 | , 18 | 41,00 | 9,00 | , 82 | 1,69 | 36,00 |
| 5,00 | 11,00 | 170,96 | , 72 | , 30 | 35,00 | 15,00 | , 70 | , 84 | 23,56 |
| 5,00 | 12,00 | 264,15 | , 86 | , 54 | 23,00 | 27,00 | , 46 | 1,06 | 32,00 |
| 5,00 | 13,00 | 55,41 | , 84 | , 12 | 44,00 | 6,00 | , 88 | , 99 | 27,00 |
| 5,00 | 14,00 | 25,91 | , 80 | , 08 | 46,00 | 4,00 | , 92 | , 66 | 27,38 |
| 5,00 | 15,00 | 95,58 | , 70 | , 28 | 36,00 | 14,00 | , 72 | , 54 | 18,71 |
| 5,00 | 16,00 | 18,09 | , 70 | , 02 | 49,00 | 1,00 | , 98 | , 66 | 25,62 |

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| 200,00 | 17,00 | 166,69 | , 00 | , 36 | 32,00 | 18,00 | , 64 | , 69 | 36,33 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 200,00 | 18,00 | 55,55 | , 00 | , 18 | 41,00 | 9,00 | , 82 | 1,16 | 59,50 |
| 200,00 | 19,00 | 11,10 | , 00 | , 00 | 50,00 | , 00 | 1,00 | 1,53 | 76,33 |
| 200,00 | 20,00 | 219,75 | , 00 | , 56 | 22,00 | 28,00 | , 44 | 1,20 | 72,67 |
| 200,00 | 21,00 | 10,40 | , 00 | , 04 | 48,00 | 2,00 | , 96 | , 55 | 27,56 |
| 200,00 | 22,00 | 38,81 | , 00 | , 16 | 42,00 | 8,00 | , 84 | 2,37 | 124,00 |
| 200,00 | 23,00 | 4,93 | , 00 | , 00 | 50,00 | , 00 | 1,00 | , 73 | 36,57 |
| 200,00 | 24,00 | 42,15 | , 00 | , 10 | 45,00 | 5,00 | , 90 | , 90 | 46,60 |
| 200,00 | 25,00 | 294,90 | , 00 | , 60 | 20,00 | 30,00 | , 40 | 2,30 | 133,50 |
| 200,00 | 26,00 | 63,48 | , 00 | , 24 | 38,00 | 12,00 | , 76 | , 56 | 28,89 |
| 200,00 | 27,00 | 128,56 | , 00 | , 26 | 37,00 | 13,00 | , 74 | 1,18 | 62,50 |
| 200,00 | 28,00 | 77,67 | , 00 | , 16 | 42,00 | 8,00 | , 84 | , 67 | 34,00 |
| 200,00 | 29,00 | 78,73 | , 00 | , 16 | 42,00 | 8,00 | , 84 | 1,99 | 100,67 |

Table 2: Simulation Results Distributed Scenario for 50 tasks.

| Dl. | Simulation | Exe. Cost | Dl. Vio. | Budget Vio. | Tasks fin. | Tasks fail. | Tasks Compl. | Resp. Times | Makespan |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 5,00 | , 00 | 83,79 | , 88 | , 04 | 48,00 | 2,00 | , 96 | 1,57 | 48,67 |
| 5,00 | 1,00 | 12,54 | , 86 | , 08 | 46,00 | 4,00 | , 92 | , 67 | 34,00 |
| 5,00 | 2,00 | 5,76 | , 92 | , 04 | 48,00 | 2,00 | , 96 | 1,03 | 52,00 |
| 5,00 | 3,00 | 120,21 | , 64 | , 36 | 32,00 | 18,00 | , 64 | , 80 | 23,80 |
| 5,00 | 4,00 | 57,12 | , 78 | , 20 | 40,00 | 10,00 | , 80 | , 68 | , 84 |
| 5,00 | 5,00 | 82,34 | , 90 | , 32 | 34,00 | 16,00 | , 68 | 29,33 |  |
| 5,00 | 6,00 | 33,16 | , 76 | , 16 | 42,00 | 8,00 | , 84 | , 94 | 41,71 |
| 5,00 | 7,00 | 91,66 | , 74 | , 18 | 41,00 | 9,00 | , 82 | , 87 | 30,50 |
| 5,00 | 8,00 | 178,46 | , 84 | , 42 | 29,00 | 21,00 | , 58 | 1,74 | 52,80 |
| 5,00 | 9,00 | 63,97 | , 74 | , 14 | 43,00 | 7,00 | , 86 | , 59 | 26,44 |
| 5,00 | 10,00 | 49,37 | , 84 | , 20 | 40,00 | 10,00 | , 80 | , 78 | 33,43 |
| 5,00 | 11,00 | 124,20 | , 86 | , 34 | 33,00 | 17,00 | , 66 | 1,29 | 47,75 |
| 5,00 | 12,00 | 194,75 | , 72 | , 56 | 22,00 | 28,00 | , 44 | 1,18 | 27,67 |













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| 200,00 | 13,00 | 44,92 | , 00 | , 18 | 41,00 | 9,00 | , 82 | , 98 | 50,60 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 200,00 | 14,00 | 50,13 | , 00 | , 16 | 42,00 | 8,00 | , 84 | , 67 |  |
| 200,00 | 15,00 | 28,95 | , 00 | , 08 | 46,00 | 4,00 | , 92 | , 66 | 32,25 |
| 200,00 | 16,00 | 17,32 | , 00 | , 06 | 47,00 | 3,00 | , 94 | , 62 | 81,88 |
| 200,00 | 17,00 | 83,93 | , 00 | , 14 | 43,00 | 7,00 | , 86 | 2,51 | 90,50 |
| 200,00 | 18,00 | 18,14 | , 00 | , 04 | 48,00 | 2,00 | , 96 | 1,21 | 63,50 |
| 200,00 | 19,00 | 32,85 | , 00 | , 04 | 48,00 | 2,00 | , 96 | 1,03 | 53,00 |
| 200,00 | 20,00 | 198,36 | , 16 | , 32 | 34,00 | 16,00 | , 68 | , 52 | 254,67 |
| 200,00 | 21,00 | 32,51 | , 04 | , 14 | 43,00 | 7,00 | , 86 | 1,69 | 239,33 |
| 200,00 | 22,00 | 27,46 | , 24 | , 06 | 47,00 | 3,00 | , 94 | , 70 | 318,86 |
| 200,00 | 23,00 | 13,44 | , 06 | , 08 | 46,00 | 4,00 | , 92 | , 83 | 216,43 |
| 200,00 | 24,00 | 74,67 | , 00 | , 18 | 41,00 | 9,00 | , 82 | , 73 | 34,38 |
| 200,00 | 25,00 | 54,59 | , 14 | , 10 | 45,00 | 5,00 | , 90 | 1,46 | 343,00 |
| 200,00 | 26,00 | 3,95 | , 14 | , 00 | 50,00 | , 00 | 1,00 | 1,09 | 333,40 |
| 200,00 | 27,00 | 26,79 | , 00 | , 04 | 48,00 | 2,00 | , 96 | 2,03 | 104,00 |
| 200,00 | 28,00 | 9,90 | , 00 | , 02 | 49,00 | 1,00 | , 98 | 2,68 | 135,50 |
| 200,00 | 29,00 | 179,57 | , 00 | , 56 | 22,00 | 28,00 | , 44 | , 48 | 27,33 |

Table 3: Simulation Results First Fit Scenario for 50 tasks.

| Dl. | Simulation | Exe. Cost | Dl. Vio. | Budget Vio. | Tasks fin. | Tasks fail. | Tasks Compl. | Resp. Times | Makespan |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 5,00 | , 00 | 162,29 | , 82 | , 44 | 28,00 | 22,00 | , 56 | , 53 | 28,12 |
| 5,00 | 1,00 | 98,48 | , 86 | , 38 | 31,00 | 19,00 | , 62 | , 64 | 33,71 |
| 5,00 | 2,00 | 93,66 | , 84 | , 24 | 38,00 | 12,00 | , 76 | 1,32 | 34,50 |
| 5,00 | 3,00 | 30,53 | , 76 | , 06 | 47,00 | 3,00 | , 94 | , 49 | 24,00 |
| 5,00 | 4,00 | 76,83 | , 88 | , 14 | 43,00 | 7,00 | , 86 | , 72 | 38,33 |
| 5,00 | 5,00 | 211,53 | , 88 | , 50 | 25,00 | 25,00 | , 50 | 1,46 | 63,67 |
| 5,00 | 6,00 | 79,21 | , 74 | , 20 | 40,00 | 10,00 | , 80 | 1,15 | 27,25 |
| 5,00 | 7,00 | 67,00 | , 80 | , 16 | 42,00 | 8,00 | , 84 | , 92 | 42,50 |
| 5,00 | 8,00 | 128,83 | , 88 | , 26 | 37,00 | 13,00 | , 74 | 1,06 | 58,00 |


















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| 100,00 | 13,00 |
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| 100,00 | 15,00 |
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| 100,00 | 17,00 |
| 100,00 | 18,00 |
| 100,00 | 19,00 |
| 100,00 | 20,00 |
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| 100,00 | 24,00 |
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| 180,00 | 26,00 |
| 180,00 | 27,00 |
| 180,00 | 28,00 |
| 180,00 | 29,00 |
| 200,00 | , 00 |
| 200,00 | 1,00 |
| 200,00 | 2,00 |
| 200,00 | 3,00 |
| 200,00 | 4,00 |
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Table 5: Simulation Results Distributed Scenario for 200 tasks.

| Dl. | Simulation | Exe. Cost | Dl. Vio. | Budget Vio. | Tasks fin. <br> 5,00 | , 00 | 567,49 | , 93 | , 36 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |

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Table 6: Simulation Results First Fit Scenario for 200 tasks.

| Dl. | Simulation | Exe. Cost | Dl. Vio. | Budget Vio. | Tasks fin. | Tasks fail. | Tasks Compl. | Resp. Times | Makespan |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 5,00 | , 00 | 112,20 | , 92 | , 09 | 182,00 | 18,00 | , 91 | , 65 | 92,33 |
| 5,00 | 1,00 | 474,98 | , 90 | , 27 | 146,00 | 54,00 | , 73 | , 89 | 79,50 |
| 5,00 | 2,00 | 413,67 | , 92 | , 20 | 161,00 | 39,00 | , 81 | , 60 | 62,57 |
| 5,00 | 3,00 | 416,16 | , 90 | , 24 | 151,00 | 49,00 | , 76 | , 69 | 92,50 |
| 5,00 | 4,00 | 483,29 | , 87 | , 26 | 149,00 | 51,00 | , 74 | , 80 | 90,20 |
| 5,00 | 5,00 | 113,13 | , 91 | , 07 | 187,00 | 13,00 | , 94 | , 70 | 60,00 |
| 5,00 | 6,00 | 544,50 | , 86 | , 39 | 122,00 | 78,00 | , 61 | , 53 | 66,67 |
| 5,00 | 7,00 | 527,46 | , 91 | , 29 | 142,00 | 58,00 | , 71 | 1,03 | 92,50 |
| 5,00 | 8,00 | 1034,03 | , 94 | , 49 | 101,00 | 99,00 | , 51 | 1,35 | 95,50 |
| 5,00 | 9,00 | 1192,58 | , 93 | , 58 | 84,00 | 116,00 | , 42 | 1,19 | 92,33 |
| 5,00 | 10,00 | 1033,47 | , 90 | , 54 | 92,00 | 108,00 | , 46 | , 89 | 56,67 |
| 5,00 | 11,00 | 606,18 | , 89 | , 32 | 136,00 | 64,00 | , 68 | 1,11 | 85,00 |
| 5,00 | 12,00 | 940,76 | , 93 | , 46 | 109,00 | 91,00 | , 55 | 1,19 | 88,50 |
| 5,00 | 13,00 | 445,74 | , 91 | , 31 | 138,00 | 62,00 | , 69 | 1,02 | 97,40 |
| 5,00 | 14,00 | 352,04 | , 88 | , 21 | 157,00 | 43,00 | , 79 | , 74 | 84,00 |
| 5,00 | 15,00 | 627,05 | , 86 | , 36 | 127,00 | 73,00 | , 64 | , 66 | 69,56 |
| 5,00 | 16,00 | 805,75 | , 94 | , 44 | 112,00 | 88,00 | , 56 | , 76 | 81,00 |
| 5,00 | 17,00 | 725,68 | , 89 | , 35 | 129,00 | 71,00 | , 65 | , 70 | 61,25 |
| 5,00 | 18,00 | 773,31 | , 90 | , 39 | 123,00 | 77,00 | , 61 | , 68 | 73,38 |
| 5,00 | 19,00 | 390,01 | , 91 | , 22 | 156,00 | 44,00 | , 78 | , 91 | 80,71 |
| 5,00 | 20,00 | 1026,97 | , 92 | , 47 | 105,00 | 95,00 | , 53 | , 94 | 97,00 |
| 5,00 | 21,00 | 513,07 | , 89 | , 37 | 126,00 | 74,00 | , 63 | , 98 | 82,40 |
| 5,00 | 22,00 | 281,04 | , 95 | , 17 | 165,00 | 35,00 | , 82 | , 75 | 93,00 |
| 5,00 | 23,00 | 1124,82 | , 88 | , 60 | 79,00 | 121,00 | , 40 | , 59 | 50,67 |
| 5,00 | 24,00 | 1184,23 | , 91 | , 56 | 88,00 | 112,00 | , 44 | , 64 | 76,50 |
| 5,00 | 25,00 | 1130,88 | , 95 | , 58 | 83,00 | 117,00 | , 41 | 1,49 | 109,50 |
| 5,00 | 26,00 | 504,14 | , 91 | , 27 | 147,00 | 53,00 | , 73 | , 98 | 69,50 |





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| $\begin{aligned} & 200,00 \\ & 200,00 \\ & 200,00 \end{aligned}$ | $\begin{aligned} & 27,00 \\ & 28,00 \\ & 29,00 \\ & \hline \end{aligned}$ | $\begin{array}{\|l} 71,05 \\ 31,43 \\ 86,43 \\ \hline \end{array}$ | $\begin{array}{r} , 03 \\ , 00 \\ , 00 \\ \hline, 0 \end{array}$ | $\begin{aligned} & , 05 \\ & , 03 \\ & , 06 \end{aligned}$ | $\begin{aligned} & 190,00 \\ & 194,00 \\ & 189,00 \end{aligned}$ | $\begin{aligned} & 10,00 \\ & 6,00 \\ & 11,00 \end{aligned}$ | $\begin{array}{r} , 95 \\ , 97 \\ , 94 \\ \hline \end{array}$ | $\begin{aligned} & 1,03 \\ & , 95 \\ & , 55 \\ & \hline \end{aligned}$ | $\begin{aligned} & 206,80 \\ & 191,00 \\ & 111,56 \end{aligned}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Table 7: Simulation Results Centralized Scenario for 600 tasks. |  |  |  |  |  |  |  |  |  |
| Dl. | Simulation | Exe. Cost | Dl. Vio. | Budget Vio. | Tasks fin. | Tasks fail. | Tasks Compl. | Resp. Times | Makespan |
| 5,00 | ,00 | 1761,81 | ,96 | ,35 | 387,00 | 213,00 | ,65 | ,82 | 211,50 |
| 5,00 | 1,00 | 1732,34 | ,96 | ,28 | 429,00 | 171,00 | ,71 | ,78 | 195,00 |
| 5,00 | 2,00 | 2413,22 | ,98 | ,45 | 330,00 | 270,00 | , 55 | 1,01 | 396,67 |
| 5,00 | 3,00 | 3143,75 | ,96 | ,52 | 286,00 | 314,00 | ,48 | , 82 | 267,67 |
| 5,00 | 4,00 | 5514,71 | ,97 | ,81 | 111,00 | 489,00 | ,18 | ,66 | 333,17 |
| 5,00 | 5,00 | 2110,58 | ,98 | ,42 | 345,00 | 255,00 | ,57 | ,81 | 300,38 |
| 5,00 | 6,00 | 2323,07 | ,96 | ,47 | 317,00 | 283,00 | ,53 | ,60 | 184,20 |
| 5,00 | 7,00 | 2925,56 | ,97 | ,55 | 270,00 | 330,00 | ,45 | ,87 | 299,75 |
| 5,00 | 8,00 | 2816,53 | ,94 | ,47 | 316,00 | 284,00 | ,53 | ,59 | 126,43 |
| 5,00 | 9,00 | 1826,45 | ,96 | ,36 | 382,00 | 218,00 | ,64 | ,84 | 350,60 |
| 5,00 | 10,00 | 3740,68 | ,99 | ,62 | 230,00 | 370,00 | ,38 | ,98 | 585,50 |
| 5,00 | 11,00 | 3434,58 | ,98 | ,62 | 228,00 | 372,00 | ,38 | 1,12 | 314,20 |
| 5,00 | 12,00 | 1061,36 | ,97 | ,21 | 471,00 | 129,00 | ,79 | 1,09 | 342,75 |
| 5,00 | 13,00 | 2603,16 | ,96 | ,52 | 287,00 | 313,00 | ,48 | , 54 | 188,44 |
| 5,00 | 14,00 | 3067,85 | ,96 | ,48 | 313,00 | 287,00 | ,52 | ,71 | 144,67 |
| 5,00 | 15,00 | 1520,01 | ,96 | ,30 | 420,00 | 180,00 | ,70 | ,63 | 280,86 |
| 5,00 | 16,00 | 2593,12 | ,96 | ,47 | 316,00 | 284,00 | ,53 | ,76 | 157,83 |
| 5,00 | 17,00 | 2749,44 | ,96 | ,50 | 299,00 | 301,00 | ,50 | ,68 | 159,80 |
| 5,00 | 18,00 | 5071,11 | ,94 | , 72 | 165,00 | 435,00 | ,28 | ,59 | 146,78 |
| 5,00 | 19,00 | 3183,54 | ,96 | ,58 | 251,00 | 349,00 | ,42 | ,67 | 304,00 |
| 5,00 | 20,00 | 2310,58 | ,97 | ,45 | 332,00 | 268,00 | ,55 | ,85 | 331,50 |
| 5,00 | 21,00 | 2992,75 | ,97 | ,54 | 275,00 | 325,00 | ,46 | ,81 | 233,00 |
| 5,00 | 22,00 | 2065,18 | ,98 | ,36 | 382,00 | 218,00 | ,64 | ,91 | 361,00 |









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| 10,00 | 23,00 | 1287,63 |
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| 10,00 | 24,00 | 3594,02 |
| 10,00 | 25,00 | 3178,76 |
| 10,00 | 26,00 | 1094,02 |
| 10,00 | 27,00 | 2751,34 |
| 10,00 | 28,00 | 1835,52 |
| 10,00 | 29,00 | 3661,97 |
| 20,00 | , 00 | 2088,62 |
| 20,00 | 1,00 | 1676,53 |
| 20,00 | 2,00 | 1718,65 |
| 20,00 | 3,00 | 3789,08 |
| 20,00 | 4,00 | 1640,12 |
| 20,00 | 5,00 | 1949,50 |
| 20,00 | 6,00 | 739,75 |
| 20,00 | 7,00 | 2080,38 |
| 20,00 | 8,00 | 3956,62 |
| 20,00 | 9,00 | 2453,44 |
| 20,00 | 10,00 | 3093,11 |
| 20,00 | 11,00 | 1315,18 |
| 20,00 | 12,00 | 2671,86 |
| 20,00 | 13,00 | 4898,24 |
| 20,00 | 14,00 | 1863,33 |
| 20,00 | 15,00 | 501,30 |
| 20,00 | 16,00 | 2378,72 |
| 20,00 | 17,00 | 1705,95 |
| 20,00 | 18,00 | 1983,47 |
| 20,00 | 19,00 | 3561,09 |
| 20,00 | 20,00 | 1546,60 |
| 20,00 | 21,00 | 2411,30 |
| 20,00 | 22,00 | 1472,46 |



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436,46
1583,88
1928,32
1090,03
294,33
2015,11
1547,43
869,15
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1142,16
687,31
549,61
3090,20
1739,84
508,39
1163,14









| 200,00 | 23,00 | 375,29 | , 23 | , 09 | 547,00 | 53,00 | , 91 | , 71 | 296,43 |
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| 200,00 | 24,00 | 1973,70 | , 45 | , 39 | 365,00 | 235,00 | , 61 | 1,39 | 458,50 |
| 200,00 | 25,00 | 721,35 | , 27 | , 16 | 506,00 | 94,00 | , 84 | 1,39 | 533,50 |
| 200,00 | 26,00 | 1509,30 | , 57 | , 30 | 421,00 | 179,00 | , 70 | 1,64 | 568,50 |
| 200,00 | 27,00 | 665,21 | , 49 | , 12 | 526,00 | 74,00 | , 88 | , 62 | 380,50 |
| 200,00 | 28,00 | 246,43 | , 56 | , 05 | 570,00 | 30,00 | , 95 | 1,97 | 1058,50 |
| 200,00 | 29,00 | 1478,21 | , 41 | , 30 | 421,00 | 179,00 | , 70 | , 51 | 331,67 |

Table 8: Simulation Results Distributed Scenario for 600 tasks.

| Dl. | Simulation | Exe. Cost | Dl. Vio. | Budget Vio. | Tasks fin. | Tasks fail. | Tasks Compl. | Resp. Times | Makespan |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 5,00 | ,00 | 2333,71 | ,97 | ,42 | 350,00 | 250,00 | ,58 | 1,37 | 135,00 |
| 5,00 | 1,00 | 1526,73 | ,98 | ,35 | 388,00 | 212,00 | ,65 | 1,88 | 173,67 |
| 5,00 | 2,00 | 2065,80 | ,97 | ,33 | 402,00 | 198,00 | ,67 | 1,73 | 151,67 |
| 5,00 | 3,00 | 1076,50 | ,97 | ,20 | 477,00 | 123,00 | ,80 | ,82 | 195,83 |
| 5,00 | 4,00 | 1179,19 | ,97 | ,24 | 457,00 | 143,00 | ,76 | 1,25 | 99,56 |
| 5,00 | 5,00 | 1484,86 | ,96 | ,29 | 426,00 | 174,00 | ,71 | 1,00 | 105,80 |
| 5,00 | 6,00 | 1035,20 | ,98 | ,20 | 482,00 | 118,00 | ,80 | ,90 | 203,43 |
| 5,00 | 7,00 | 2490,63 | ,96 | ,40 | 362,00 | 238,00 | ,60 | 1,02 | 93,00 |
| 5,00 | 8,00 | 1779,66 | ,97 | ,36 | 384,00 | 216,00 | ,64 | 1,84 | 254,75 |
| 5,00 | 9,00 | 2284,34 | ,97 | ,38 | 370,00 | 230,00 | ,62 | ,75 | 106,17 |
| 5,00 | 10,00 | 2288,47 | ,97 | ,38 | 375,00 | 225,00 | ,62 | ,95 | 148,00 |
| 5,00 | 11,00 | 557,80 | ,95 | ,12 | 530,00 | 70,00 | ,88 | ,95 | 109,33 |
| 5,00 | 12,00 | 2240,93 | ,96 | ,39 | 368,00 | 232,00 | ,61 | ,75 | 121,62 |
| 5,00 | 13,00 | 4167,69 | ,97 | ,61 | 232,00 | 368,00 | ,39 | 1,09 | 139,57 |
| 5,00 | 14,00 | 2615,12 | ,96 | ,43 | 342,00 | 258,00 | , 57 | 1,37 | 118,14 |
| 5,00 | 15,00 | 2356,97 | ,96 | ,45 | 333,00 | 267,00 | ,56 | 1,05 | 162,60 |
| 5,00 | 16,00 | 2793,92 | ,98 | ,44 | 334,00 | 266,00 | ,56 | 3,80 | 118,80 |
| 5,00 | 17,00 | 1665,56 | ,95 | ,33 | 401,00 | 199,00 | ,67 | ,89 | 172,25 |
| 5,00 | 18,00 | 1709,75 | ,96 | ,31 | 415,00 | 185,00 | ,69 | ,69 | 220,00 |
























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| 200,00 | 19,00 | 191,24 | , 16 | , 04 | 574,00 | 26,00 | , 96 | , 69 | 983,40 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 200,00 | 20,00 | 127,29 | , 21 | , 03 | 583,00 | 17,00 | , 97 | , 82 | 1519,50 |
| 200,00 | 21,00 | 349,14 | , 64 | , 08 |  | 552,00 | 48,00 | , 92 | 3,51 |
| 200,00 | 22,00 | 369,14 | , 26 | , 06 | 566,00 | 34,00 | , 94 | , 84 | 1551,00 |
| 200,00 | 23,00 | 405,94 | , 03 | , 06 | 562,00 | 38,00 | , 94 | , 78 | 2088,17 |
| 200,00 | 24,00 | 1775,16 | , 08 | , 37 | 378,00 | 222,00 | , 63 | , 57 | 1090 |
| 200,00 | 25,00 | 585,40 | , 30 | , 15 | 507,00 | 93,00 | , 84 | , 81 | 883,80 |
| 200,00 | 26,00 | 44,51 | , 23 | , 00 | 598,00 | 2,00 | 1,00 | , 85 | 1364,67 |
| 200,00 | 27,00 | 587,64 | , 47 | , 11 | 532,00 | 68,00 | , 89 | 1,34 | 1111,00 |
| 200,00 | 28,00 | 424,16 | , 00 | , 10 | 542,00 | 58,00 | , 90 | 1,28 | 86,00 |
| 200,00 | 29,00 | 444,12 | , 53 | , 09 | 544,00 | 56,00 | , 91 | , 69 | 422,29 |

Table 9: Simulation Results First Fit Scenario for 600 tasks.

| Dl. | Simulation | Exe. Cost | Dl. Vio. | Budget Vio. | Tasks fin. | Tasks fail. | Tasks Compl. | Resp. Times | Makespan |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 5,00 | , 00 | 1012,03 | , 98 | , 21 | 475,00 | 125,00 | , 79 | , 89 | 221,67 |
| 5,00 | 1,00 | 1927,69 | , 97 | , 37 | 380,00 | 220,00 | , 63 | 1,17 | 327,00 |
| 5,00 | 2,00 | 2546,64 | , 95 | , 50 | 299,00 | 301,00 | , 50 | , 62 | 160,57 |
| 5,00 | 3,00 | 2358,19 | , 96 | , 40 | 363,00 | 237,00 | , 60 | , 86 | 151,25 |
| 5,00 | 4,00 | 2793,01 | , 97 | , 51 | 292,00 | 308,00 | , 49 | , 76 | 250,29 |
| 5,00 | 5,00 | 3080,14 | , 97 | , 54 | 274,00 | 326,00 | , 46 | , 81 | 144,00 |
| 5,00 | 6,00 | 2238,23 | , 95 | , 35 | 390,00 | 210,00 | , 65 | , 66 | 138,00 |
| 5,00 | 7,00 | 2577,05 | , 97 | , 47 | 319,00 | 281,00 | , 53 | , 67 | 189,00 |
| 5,00 | 8,00 | 4335,22 | , 96 | , 61 | 231,00 | 369,00 | , 39 | 1,31 | 150,20 |
| 5,00 | 9,00 | 1869,42 | , 96 | , 36 | 382,00 | 218,00 | , 64 | , 92 | 110,60 |
| 5,00 | 10,00 | 3789,97 | , 97 | , 66 | 205,00 | 395,00 | , 34 | 1,03 | 209,40 |
| 5,00 | 11,00 | 1826,34 | , 96 | , 34 | 398,00 | 202,00 | , 66 | 1,22 | 138,00 |
| 5,00 | 12,00 | 2316,16 | , 98 | , 42 | 346,00 | 254,00 | , 58 | 1,21 | 178,83 |
| 5,00 | 13,00 | 2597,97 | , 98 | , 42 | 348,00 | 252,00 | , 58 | , 86 | 269,25 |
| 5,00 | 14,00 | 936,61 | , 95 | , 20 | 480,00 | 120,00 | , 80 | , 68 | 195,56 |








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 65,00
40,00
30,00
103,00
41,00
14,00
87,00
8,00
14,00
49,00
32,00
230,00
35,00
16,00
104,00
52,00
87,00
16,00
5,00
126,00
16,00
124,00
76,00
90,00
9,00
49,00
19,00
144,00
21,00
11,00





326,89
370,14
1181,14
376,00
371,25
418,57
388,33
412,00
858,20
309,00
414,83
619,17
1003,80
386,71
127,25


17,00
40,00
161,00
13,00
34,00
15,00
50,00
64,00
39,00
224,00
84,00
24,00
141,00
62,00
67,00
583,00
560,00
439,00
587,00
566,00
585,00
550,00
536,00
561,00
376,00
516,00
576,00
459,00
538,00
533,00


138,79
282,84
1452,92
134,43
229,90
143,51
444,75
499,11
337,99
1872,67
619,71
209,59
1276,08
458,59
482,13



[^0]:    ${ }^{1}$ http://www.cloudbus.org/cloudsim/

[^1]:    ${ }^{1}$ https://aws.amazon.com/
    ${ }^{2}$ https://cloud.google.com/
    ${ }^{3}$ https://azure.microsoft.com/

[^2]:    ${ }^{4}$ https://azure.microsoft.com

[^3]:    ${ }^{5}$ https://msdn.microsoft.com/en-us/library/ff524509(v=vs.93).aspx

[^4]:    Algorithm 3.1: Process of a PSO

    1. Initialize the population of particles with random positions and velocities.
    2. Compare the particle's fitness value with its pbest and keep the better one in pbest.
    3. Compare the pbest from all particles with the global gbest and keep the best value in gbest.
    4. Update position and velocity of each particle according to Equations 3.7 \& 3.8 .
    5. Repeat step 2 to 4 until stopping criterion is met.
