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Bachelor's thesis

Design and implementation of a scalable server for parallelization of optimization algorithms execution

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Design and implementation of a scalable server for parallelization of optimization algorithms execution

Pokyny pro vypracování:

Large-scale optimization problems are non-trivial to solve and require a significant amount of computational resources as well as computational time to find a solution. The challenge is to solve not only a single task but a multitude of them in a parallel manner. Additionally, the tasks are non-homogeneous, often describing a different problem. This problem can be solved by designing and intelligent scheduler able to schedule such tasks on a distributed computational platform.
The goal of the thesis is:
Study the state-of-the-art approach to computational tasks scheduling. Study various types of optimization problems and approaches and understand their computational needs. Study the distributed scalable architecture and approaches to schedule tasks on such architecture. Design a scheduling and load-balancing module able to ingest various optimization tasks and schedule them with respect to several criteria. Implement the scheduler. Evaluate the scheduler on a number of scenarios.

Seznam doporučené literatury:

[1] Boyd, S., & Vandenberghe, L. (2004). Convex optimization. Cambridge university press.
[2] AWS. Load Balancing, User Guide. Amazon. Online.
https://docs.aws.amazon.com/elasticloadbalancing/latest/userguide/elb-ug.pdf.
[3] Iqbal, M. A., Saltz, J. H., & Bokhart, S. H. (1986). Performance tradeoffs in static and dynamic load balancing strategies.

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Lukáš Forst

Declaration

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Abstrakt

Velké optimalizační úlohy nejsou jednoduché a pro nalezení řešení vyžadují velké množství výpočetního výkonu, stejně jako výpočetního času. Proto je výzvou je vyřešit paralelně a v co nejkratším možném čase. Optimalizační problémy nejsou homogenní skupina, ale popisují často kompletně odlišnou doménu a tedy mohou být velice různorodé. Problém exekuce optimalizačních programů a jejich výkonové náročnosti, lze řešit za použití inteligentního plánovače, který umožňuje naplánovat samotné spuštění úlohy v distribuovaném výpočetním prostředí.
Tato práce se zabývá matematickou formalizací takového problému a představuje implementaci plánovače a rozvrhovače zátěže speciálně navrženého a vyvinutého pro optimalizační algoritmy.

Klíčová slova vyvažování a distribuce zátěže, optimalizační algoritmy, Kotlin, Ktor, Docker

Abstract

Large-scale optimization problems are non-trivial to solve and require a significant amount of computational resources as well as computational time to find a solution. The challenge is to solve not only a single task but a multitude of them in a parallel manner. Additionally, the tasks are non-homogeneous, often describing a different problem. This problem can be solved by designing and intelligent scheduler able to schedule such tasks on a distributed computational platform.
This work introduced the mathematical formalization and the implementation of the load balancing system specifically designed and developed for the optimization algorithms.

Keywords load balancing, optimization algorithms, Kotlin, Ktor, Docker

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Chapter 1

Introduction

The globalization of the world's economies is a major challenge to local industry and it is pushing the manufacturing sector to the transformation called *Industry 4.0* [1]. In order to become more competitive, manufacturers need to embrace emerging technologies, such as advanced analytics, artificial intelligence and mathematical optimization to improve their efficiency and productivity.

Specifically manufacturing industry sector, which have high production costs, faces multiple problems, where employing mathematical optimization can reduce cost or improve efficiency of the process. Taking as en example the car manufacturers, there are many processes, that can be optimized to reduce their cost or to use needed resources more efficiently, such as an internal logistics, car parts transportation, parts stocking, cars manufacturing and the allocation of the various types of resources. These optimization challenges are often solved by the proprietary software systems with included optimization engine, where the one problem domain is usually handled by the single program operating specifically with such domain.

These applications typically have an user interface for the data visualization and an engine running an optimization algorithm. Although the data visualization part of the application does not require powerful hardware, the immense complexity of the mathematical optimization problems and thus the performance requirements for such optimization engine solving them, are not always satisfiable. Moreover, the computer performance is finite resource and it cost money paid for the computer components or for the electricity used. For that reasons, the optimization software systems have often limited access to the computer resources. In addition, this computer performance is not used all the time, since the typical usage of such application lays mainly in data visualization, hence the performance, required only when the optimization engine is running, is unused.

Using such software architecture seems to be highly inefficient, since the instances, that are in time t running the optimization algorithm, are over-

whelmed and in the same time t, the applications, that are not running the optimization tasks, do not use their powerful computer resources at all.

The potential solution for this problems lays in microservices architecture, where the parts of the applications are independent and able to run separately. Using this approach enables distributed computing and therefore outsourcing the demanding optimization engine to more powerful servers. This approach solves the lack of resources for the optimization engine on the less powerful servers, but it also introduce new challenge in the load balancing of the servers, where the optimization engine is being executed.

In this thesis we would like to present the load balancer specifically developed for the optimization algorithms, which should minimize resources wasting and increase the performance using correct utilization distribution across the multiple instances of such algorithms.

1.1 Thesis goals

To summarize the previous introduction, the main goals of the thesis were set as follows.

Study the state-of-the-art approach to computational tasks scheduling

This thesis extensively studies and describes state of the art algorithms used for computational task scheduling and load balancing in section 2.1. It also presents technologies used, to solve such problems. The difference between the state-of-the-art load balancing strategies and why the thesis proposes and implements the new technology instead of using the existing one is presented in section 2.1.3.

Study various types of optimization problems and approaches and understand their computational needs

The thesis brings an overview of and describes various optimization problems, techniques and algorithms that are being used in the real-life situations to solve diverse industries problems in section 2.2.

Study the distributed scalable architecture and approaches to schedule tasks on such architecture

The distributed architecture study is presented in section 5.1. This section also introduces the overall distributed architecture of the load balancer including the simulation module.

Design a scheduling and load-balancing module able to ingest various optimization tasks and schedule them with respect to several criteria

The complex problem of the load balancing of the optimization tasks is formalized in chapter 3. Based on the problem formalization, solution design including the final load balancing algorithm is introduced in chapter 4.

Implement the scheduler

The load balancing module design from chapter 4 is used for load balancing module implementation in chapter 5. The very same chapter contains an overview of the module architecture in the section 5.1. The architecture was designed to keep future infrastructure development in mind and thus few out of scope future steps were outlined in section 7.1.

Evaluate the scheduler on a number of scenarios

The chapter 6 describes the way, how the scheduler and the load balancing system was tested. It also describes in section 6.2 how the runtime data of optimization algorithms were collected. The next section 6.3 presents the scheduler evaluation.

Apart from the original goals of the thesis, which were set in the assignment, many out of scope and future goals arose during the formalization, research and implementation. These goals and an overviews how to achieve them are outlined in the section 7.1.

Chapter 2

State of the art

2.1 Load Balancing

Load balancing is technique for a division of processing work in the distributed environment of execution units [1] with aim to deliver faster service with higher efficiency. It improves the distribution of workloads across the whole environment and thus balances resources usage while maximizing throughput and minimizing response time. Load balancer is typically either dedicated *hardware device* or *software program*.

A **hardware** load balancer is a dedicated hardware device which distributes network traffic across a cluster of servers [2]. These devices are used mainly in the data centers to ensure equal distribution of traffic between the application servers. Main benefit of using hardware load balancer is zero balancing overhead on the host machines, because all decisions are made on dedicated hardware specially developed for such tasks.

A **software** load balancer is a program operating on the application server with the same aim as hardware load balancer. Main advantage of the software load balancing is that it can be heavily customized and deployed to its own server. This paper will discuss only software load balancing approach.

In general, software load balancing algorithms can be classified as either *static* or *dynamic*.

2.1.1 Static Load Balancing

Static load balancing is an approach where system information are provided a priori and load balancer does not use performance information about

[1] In general, execution unit can be CPU, network links, storage devices or other devices, in this paper *execution unit* or also referred as *execution node* or as *host* is a computer executing assigned job

execution node [2], to make distribution decisions. The performance possibilities and the load of the execution point (or node) are not taken in account when decision - where to execute current task - is being made, because load-balancing decisions are made at compile time. When a decision is made, no other interaction with executing node, regarding the current task, is being made. In other words, once the load is allocated to the execution node, it cannot be transferred to another node. Static load balancing method is to reduce the overall execution time of a concurrent program while minimizing the communication delays [3]. The main advantage of static load balancing methods is mainly the fact, that there is minimal communication delay between system nodes and therefore execution overhead is minimized to almost zero. For that reason is static load balancing mainly used in the fields, where server response is crucial such as serving a web page.Also the implementation of some static load balancing algorithm is straightforwards, since the used methods are very simple.

The main disadvantage of static load balancing is that it does not take in account current state of the system, when making decision. This could potentially lead to performance issues in the whole system because some nodes can be overloaded although others are not working at all.

Another drawback of this approach is that hardware resources are allocated only once in the execution time. Since optimization jobs are very heterogeneous, they sometimes have different power requirements during the execution. For example *TASP*[3] uses only one thread when creating feasible plan in the first algorithm iteration - this task relays only on single core performance. However, when first iteration is completed, all following can be done by multiple threads, therefore it could be useful to execute first iteration on a machine with better single core performance and then transfer algorithm into machine focused on multiple threads execution. This is something that can not be done while using static load balancing.
Following static load balancing algorithms are commonly used.

First Alive

First alive or also called *Central Manager* algorithm uses the concept of a primary server and backup servers [4]. All tasks are scheduled to be executed on primary server unless the primary server is down. Then the load will be forwarded to first backup server. This algorithm has almost zero level of inner process communication, which leads to better performance when there are lots of smaller tasks.

[2]Execution node - Server executing task which is being scheduled by load balancer. In our case, this task is solving optimization problem by solver.

[3]**Task and Asset Scheduling Platform** - proprietary optimization software developed by Blindspot Solutions, described in section 2.2.2

Round Robin

Round Robin algorithm which distributes work load evenly to all nodes. It is being done in round robin order, where load is distributed to each node in circular order without any priority. Round Robin is esy to implement and as well as *First alive* algorithm has almost none inner communication overhead. This algorithm performs best when tasks have equal, or at least similar, processing time.

Weighted Round Robin

Weighted round robin algorithm maintains a weighted list of servers and forwards new connections in proportion to the weight, or preference, of each server. This algorithm uses more computation times than the round robin algorithm. However, the additional computation results in distributing the traffic more efficiently to the server that is most capable of handling the request [4].

Threshold Algorithm

Threshold algorithm - execution nodes keep private copy of the system's load, when the load state of a node exceeds a load level limit, node sends message to all remote nodes, that it is overloaded. If the local state is not overloaded then the load is allocated locally. Otherwise a remote node, that is not overloaded, is selected and if no such node exists it is also allocated locally. This algorithm has low inter process communication and large number of local process allocations. The later reduces the overhead of remote process allocation and the overhead of remote memory access, which leads to performance improvements [5].

Least Connections

Least connections algorithm maintains a record of active server connections and forward a new connection to the server with the least number of active connections [4]. This can be generally useful while having many concurrent requests, that can be dispatched quickly.

Randomized Algorithm

Randomized algorithm uses random selection of the execution node without having any information about it.

2.1.2 Dynamic Load Balancing

Unlike static load balancing algorithms, dynamic algorithms use runtime state information to more informative decisions while distributing the jobs.

They monitor changes on the system work load and take it in account when decision, where to execute job, is being made. The process of monitoring the system is not stopped after execution job started and if circumstances change, job execution can be transferred to another system node which then proceeds with execution.

While many different load balancing algorithms have been proposed, there are four basic steps that nearly all algorithms have in common [6].

1. Monitoring workstation performance (load monitoring)

2. Exchanging this information between workstations (synchronization)

3. Calculating new distributions and making the work movement decision (rebalancing criteria)

4. Actual data movement (job migration)

Dynamic load balancing algorithms can be divided into two groups based on their control form, or in other words, where load balancing decisions are made [6].

- Centralized - a single node in the network is responsible for all load distribution

- Distributed - all nodes ale equal

While in centralized scheme are decisions made in one master workstation, in distributed scheme, the load balancing algorithm runs on all nodes and each node balances itself. Each of this approach has its own ups and downs, centralized scheme can be potential performance bottleneck since it relies on one system node, on the other hand distributed scheme has communication overhead, because it requires broadcast communication between all algorithm instances.

The main advantage of dynamic load balancing is that it allows changing execution node in runtime. For that reason it is possible to change hardware characteristics according to the job execution phase. For example execute initial phase of optimization algorithm on machine with powerful single core performance and then move the job to the machine with multiple, less powerful, cores to let it run in parallel.Also as a result of runtime scheduling, dynamic load balancing algorithms tend to provide a significant improvements in performance over static algorithms. However, this comes at the additional cost of collecting and maintaining load information [6]. For that reason dynamic load balancing suites better for long running tasks, which can be managed and distributed better, than for fast queries.

Dynamic load balancing strategies

There are three major parameters which usually define the strategy a specific load balancing algorithm will employ. These three parameters answer three important questions [6]:

1. Who makes the load balancing decision?
2. What information is used to make the load balancing decision?
3. Where the load balancing decision is made?

Question number 1 is answered based on whether a **sender-initiated** or **receiver-initiated** policy is employed. In *sender-initiated* policies, congested nodes attempt to move work to lightly-loaded nodes. In *receiver-initiated* policies, lightly-loaded nodes look for heavily-loaded nodes from which work may be received [6].

Question 'What information is used to make the load balancing decision¿ is answered by following policies - **global** and **local**. When algorithm uses *global* policy, the load balancer uses the performance profiles of all execution nodes connected to the network. When using *local* policy, only local [4] nodes are taken in account while creating performance profile of the system.

The last parameter - 'where the load balancing decision is made' - is answered by used control form, as mentioned previously, dynamic load balancing algorithms are divided into two groups based on their control form - **centralized** and **distributed**.

I would like to present two general dynamic load balancing algorithms - *Central Queue Algorithm* and *Local Queue Algorithm.*

Central Queue Algorithm

Central queue algorithm is based on centralized receiver-initiated load balancing strategy. It uses a cyclic FIFO queue on the main host to store new activities[5] and unfulfilled requests. New activity request is inserted into queue and here it is stored until some execution node picks it up.

Whenever a request for an activity (which is send by executing node in the case when its load has fallen bellow specified threshold) is received by the queue manager[6], it removes the first activity from the queue and sends it to the requester. If the queue is empty, the request is buffered, until a new activity is available. If a new activity arrives at the queue manager while there

[4] Workstations are usually divided into groups, in this context *local* means in the same group of workstations

[5] Activities - jobs to be executed, in our case optimization job

[6] Queue manager - central server which manages queue

are unanswered requests in the queue, the first such request is removed from the queue and the new activity is assigned to it.

When a execution node load falls under the threshold, the local load manager sends a request for a new activity to the central load manager (which manages the central system queue). The central load manager answers the request immediately if a ready activity is found in the queue, or queues the request until a new activity arrives [7].

Local Queue Algorithm

Local queue algorithms uses distributed receiver-initiated strategy.

Its main feature is, that it supports dynamic process migration.This algorithm in the first step uses static allocation of all new processes - all processes are allocated to under loaded hosts. In the second step the process migration is initiated by a host when its load falls under predefined threshold[7]. In such case, the execution node attempts to get several processes from remote hosts. It randomly sends requests with the number of local ready processes to remote load managers. When a load manager receives such a request, it compares the local number of ready processes with the received number. If the former is greater than the latter, then some of the running processes are transferred to the requester and an affirmative confirmation with the number of processes transferred is returned. [7]

Local queue algorithm is distributed load balancing algorithm where each execution node requests a new activity when it is under loaded. The main advantage of using such algorithm is the fact, that there is no central point, where all requests are managed and distributed to another segments of system. For that reason is this particular algorithm copes and performs well under an increased or expanding workload.

2.1.3 Load Balancing for Optimization Algorithms

In general, load balancing algorithms don't use information about what exactly is being executed on the execution nodes. This is because they are working mainly on the network layer and thus don't need that information. Also, they are mainly designed to be generic - to be used with any system and to be suitable for every environment. From the load balancer point of view, everything behind load balancing layer of the system is a black box.

Because there is no knowledge about the algorithms operating on the execution nodes, load balancing algorithm can not make fully informed decision about the job execution. However, this paper focus on the load balancing and execution scheduling of optimization algorithms, therefore, unlike generic load balancing solutions, proposed load balancer **have** the information about execution algorithms on the host machine and thus load balancing decision

[7] This threshold can be defined by the user and it is an input for the algorithm

are more informed. More informed load balancing decisions could potentially lead to better performance and costs reduction as well as greater capacity of whole system.

Since load balancer is aware of algorithms running on the hosts, it can take in account an execution criteria which can be specified (such as execution time) or at least estimated (how much memory will be needed according to the domain size) in advance to make even more informed balancing decision when scheduling the job execution. This is also the main difference between the generally used and existing load balancing software and a solution proposed in this paper.

2.2 Optimization Algorithms

In this section thesis presents various optimization techniques and existing solvers implementations, that can be used to solve such optimization problems.

2.2.1 Linear Optimization

Linear optimization (or linear programming) is a method to achieve the best outcome in a mathematical modelwhose requirements are represented by linear relationships. The algorithms are widely utilized in company management, such as planning, production, transportation, technology and other issues.

The main benefit of linear optimization is that it provides the best possible solution, because optimization algorithms are guaranteed to provide optimal solution. Although almost everything can be represented as linear problem, linear programming solvers could be unable to provide solution since, in the most cases, computation time grows exponentially. Even though there are solvers that are able to provide ϵ (partial) solution,this solution can be (and in most cases is) unusable, because is is not optimal at all.

There are plenty of linear programming solvers available. I would like to highlight following two optimization kits.

GLPK

GNU - *GNU Linear Programming Kit* is a software package intended for solving large-scale linear programming (LP), mixed integer programming (MIP), and other related problems. It is a set of routines written in ANSI *C* and organized in the form of a callable library [8]. Although originally is GLPK written in *C* programming language, there is an independent project, which provides Java-based interface for execution of GLPK via Java Native Interface. [8]

Google OR-Tools

Google OR-Tools - OR-Tools is an open source software suite for optimization, tuned for tackling the world's toughest problems in vehicle routing, flows, integer and linear programming, and constraint programming [9]. Tools contain *Glop* which is Google's custom linear solver. One of the greatest advantages of Google OR-Tools is great API supporting multiple programming languages - *C++, Python, C#* and *Java*.

[8] Java Native Interface - Interface provided by Java platform to run and integrate non-Java language libraries

2.2.2 Heuristic algorithms

Heuristics algorithms (or HA) are designed to solve optimization problems fasterand more efficient fashion than Linear Optimization methods by using different kinds of heuristics and metaheuristics. In exchange for that, algorithms sacrifice optimality, accuracy, precision, and completeness. Thus solution provided by HA is not guaranteed to be optimal. HA are often used to solve various types of NP-complete problems such as Vehicle Routing, Task Assignment, Job Scheduling or Traveling Salesmen Problem. Heuristic algorithms are most often employed when approximate solutions are sufficient and exact solutions are necessarily computationally expensive [10].

The main advantage of heuristic algorithms is that they provide quick feasible solution. Because the implementation of HA is easier than LP and they provide at least feasible solution for optimization problems, they are solving, they are widely used in organizations that face such optimization problems. The main downside of HA is the fact, that they can't guarantee that the found solution is the optimal one.

I would like to mention two implementations of heuristics algorithms - OptaPlanner and TASP.

OptaPlanner

OptaPlanner is an open source generic heuristics based constraint solver. It is designed to solve optimization problems such as Vehicle Routing, Agenda Scheduling etc. While solving optimization task, it combines and uses various optimization heuristics and metaheuristics such as Tabu Search or Simulated Annealing.

OptaPlanner is written in pure Java and runs on JVM, therefore it can be used as Java library.

TASP

Task and Asset Scheduling Platform is a lightweight framework developed by Blindspot Solutions [11] designed to solve a large variety of optimization and scheduling problems from the area of logistics, workforce management, manufacturing, planning and others. It contains a modular, efficient planning engine utilizing latest optimization algorithms. TASP is delivered as a software library to be used through its API in applications which require powerful scheduling capabilities.

It is written in Kotlin which runs on JVM, therefore it can be easily used as library to any JVM based project.

Chapter 3

Problem formalization

The problem with implementation of optimization algorithms in applications is that their performance requirements are quite high and are fully utilized only while working. Optimization algorithm is not running all the time and for that reason hardware resources are mainly unused. These unused resources could be potentially used by another instance of algorithm or can be shutdown completely to reduce hosting costs. Also adding more time to the job execution does not always bring better solution but it certainly costs more.

The figure 3.1 displays standard case, when application is deployed on the server. Because the application uses optimization algorithm, the server must be powerful enough to deliver suitable results. This also means, that the server resources must be allocated to the application and to nothing else, which leads to the resource wasting.

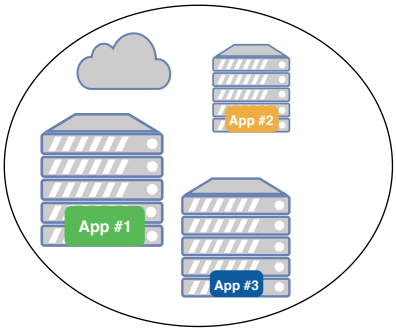

Figure 3.1: Problem visualization

The next figure 3.2 visualizes scenario when the load balancer is used. Instead of using powerful servers for each of the applications, it is enough to use small server or even deploy multiple applications on the one machine. This can be done thanks to the outsourcing of the optimization jobs to the external

servers with more computational power. The circles are optimization jobs,

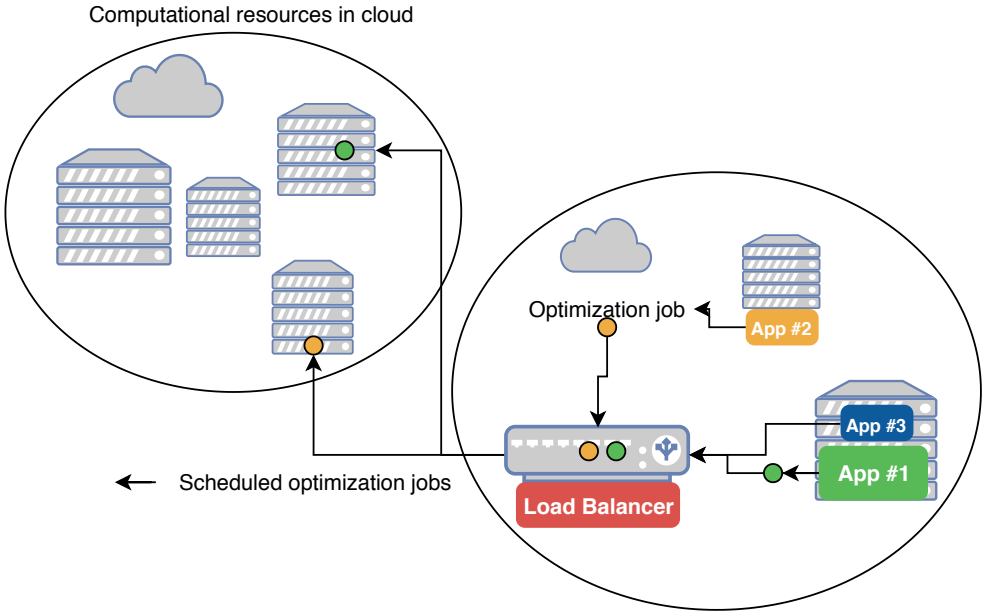

Figure 3.2: Problem visualization with the load balancer

that were triggered by the same colored applications and are being executed on the different servers in the cloud.

Moreover, as can be seen in the figure 3.2, these servers do not need to be allocated all the time. Most resources providers, such as AWS [12] or Azure [13] allow to reallocate hardware on the fly. This leads to potentially significant cost savings and ultimately to the more effective infrastructure.

3.1 Formal definition

Following definition implies, that it can be represented as an Integer Linear Programming (ILP) problem. Although, it is not entirely formalized, it is only mechanical work to transcript all implications into equations. For that reason, and better readability, we left the implications.

3.1.1 Variables Definition

Following indexes, inputs and variables are used in the optimization criteria.

Indexes

- j - index used to identify something related to the execution job, in real world this is most likely job id, located in the right upper corner - x^j, set of all jobs in the system is represented by J
- r - index used to identify resources, written in the left upper corner - ${}^r x$, set of resources is represented by R
- t - right bottom index represents time - x_t

Input

Input which is specified before executing optimization job by the user outside of the system. When new execution job is requested - this is done by the user, or client application, following data should be provided.

- D^j - maximal duration of the job execution which cannot be exceeded
- P^j - maximal used resources cost per job, or in other words highest possible price paid for the job execution which cannot be exceeded

There are also constants defined before load balancer start up.

- ${}^r c$ - cost of the using particular resources per one time unit

Each of the previously mentioned variable must be non-negative.

Program Output

Apart from result of the underlying optimization algorithm, following data are returned to user after successful job execution.

- T^j - time taken, duration of the actual job execution
- C^j - resource costs, how much money was actually paid for the job execution

Variables

- v_t^j - value (i.e. cost of the scheduled plan) of the job j at the time t Value is greater than zero and it is non-increasing during the time.

$$\forall t, j : v_t^j \geq v_{t+1}^j > 0 \tag{3.1}$$

  It is non-increasing because optimization algorithms return always best found solution, so when worse solution, than currently best one, is found, returned is still the best solution found.

- ${}^r x_t^j$ - represents assignment of the resources r at time t to job j

$${}^r x_t^j = \{0, 1\} \tag{3.2}$$

  Each x is either 1 = indexed resources are assigned to the job at given time or 0 = given combination does not have assignment. We assume that each job has only one such assignment at one time, which effectively means that this job is executed on the single computation node. This is defined by following constraint:

$$\forall j, t : \sum_{r \in R} {}^r x_t^j \leq 1 \tag{3.3}$$

- ${}^r \Delta_t^j$ - enhancement of the value v with resources r on the job j per time t.

$${}^r \Delta_t^j = {}^r |v_t^j - v_{t-1}^j| \cdot {}^r x_t^j \tag{3.4}$$

  It is improvement of the solution value v which can be achieved by using resources r at time t. This value is always non-negative since optimization algorithm always stores best found solution, and therefore $\forall j, t, r : {}^r \Delta_t^j \geq 0$. ${}^r x_t^j$ ensures that only resources, that are actually used, are taken in account.

- S_t^j - reward for improving solution value until time t per job j. Accumulation of enhancements ${}^r \Delta_t^j$ through all resources r and time units t.

$$S_t^j = \sum_t \sum_{r \in R} {}^r \Delta_t^j \tag{3.5}$$

- C_t^j - defines how much execution of job j cost from the beginning of the execution until time t. Sum of all allocated resources for their time for the particular job.

$$C_t^j = \sum_t \sum_{r \in R} {}^r c \cdot {}^r x_t^j \tag{3.6}$$

  Because C_t^j is defined as sum and ${}^r c$ is non-negative, it is true that $\forall j, t : C_{t+1}^j \geq C_t^j$. Input of the program specifies maximal cost paid for

job execution as a P^j, therefore it must be enforced by the system that this cost will not be exceeded. This constraint can be defined as follows.

$$\forall t, j : \; P^j \leq C_t^j \implies \sum_{t+1}^{\infty} \sum_{r \in R} {}^r x_t^j = 0 \tag{3.7}$$

Which effectively means that when cost of job execution C_t^j has reached maximal defined cost P^j, no resources can be assigned to this job.

- t - time, it is not only index but also variable, there are also constraints regarding time - since client application can specify deadline to job D^j, there must be additional constraint for job execution in a matter of resources assignment.

$$\forall t, j : \; D^j \leq t \implies \sum_{t+1}^{\infty} \sum_{r \in R} {}^r x_t^j = 0 \tag{3.8}$$

When maximal time is exceeded, no additional resources can be assigned to the job execution, which could be defined by following constraint.

3.1.2 Resources reconfiguration

System should be capable of changing resources assignment per job in the runtime. This will help to distribute performance according to the current nodes load across whole network. Unfortunately, it is not always possible to reconfigure resources assignment while scheduling is being performed. Therefore there must be at least one time unit, between different resources assignment, where no resources are assigned to the job. In other words, if resources reconfiguration is triggered in time t then $\sum_{r \in R} {}^r x_t^j = 0$. This can be formalized as:

$$\sum_{r \in R} {}^r x_t^j = 1 \implies \forall r \in R : \; {}^r x_t^j - {}^r x_{t+1}^j \geq 0 \tag{3.9}$$

3.1.3 Optimization criteria

The main goal of the system is to minimize outcome value of the underlining optimization algorithm and at the same time to minimize cost of used resources. We can optimize single job or sum of outcomes from all jobs in the system at once. First approach provides possibility to control and optimize outcome of a particular job, which is an advantage for single client (job owner), but it does not necessarily means that it is optimal for the whole system and vice versa. Optimization criteria for the single job at particular time t is then maximization of weighted difference between the value enhancement reward and cost paid for the enhancement, which can be described by following equation.

$$\max crit_t^j = \alpha S_t^j - (1 - \alpha) C_t^j \qquad 0 \leq \alpha \leq 1 \tag{3.10}$$

For optimization of system-wide resources and costs, all jobs execution optimization is then defined like a weighted sum of all rewards per jobs lowered by sum of all resources costs across the set of all jobs.

$$\max crit_t = \alpha \sum_{j \in J} S_t^j - (1 - \alpha) \sum_{j \in J} C_t^j \qquad 0 \leq \alpha \leq 1 \tag{3.11}$$

Based on the previous equation, it is possible to define time independent optimization criterion.

$$\max crit = \sum_{t}^{\infty} crit_t \tag{3.12}$$

3.2 Resulting problem

Proposed formal definition (3.1) implies that problem is integer linear problem with job execution cost as its main optimization criteria. These problems are solvable by various types of mixed integer linear programming solvers. Linear optimization and its characteristics are outlined in previous section 2.2.1.

However, apart from load balancing decisions, the problem brings another challenges in time series prediction during the job executions. This problem arises because algorithm, by definition presented in section 3.1, estimates enhancement of the job's solution value when the job uses particular resources in the next time period. In other words, algorithm needs to estimate impact of using particular resources in the next time period on solution value function development. Therefore in time t it needs to estimate value of the solution value function v_{t+1}^j. The definition in section 3.1 describes it as ${}^r\Delta_t^j$ variable. Based on the ${}^r\Delta_t^j$ value, the reward for improving solution value S_t^j is computed. This reward is then used when the load balancing decisions are being made to reflect the suitability of current execution plan solution.

Chapter 4

Solution design

Presented problem can be solved using many possible approaches, We have decided to use mathematic optimization for running algorithms values predictions and heuristic algorithm for load balancing decisions.

4.1 Solution value prediction

To have the most informed decisions while creating load balancing decisions, algorithm creating these decisions needs to be able to estimate the impact of an assigned resources to the development of the solution value of the job. Therefore in time t it needs to estimate value of the solution value function v_{t+1}^{j}. The definition in section 3.1 describes this estimated impact as ${}^{r}\Delta_{t}^{j}$ variable. The reward for improving solution value S_{t}^{j} is then computed based on this ${}^{r}\Delta_{t}^{j}$ value. This reward is then used when the load balancing decisions are being made to reflect the suitability of the current execution plan solution.

Unfortunately, it is practically impossible to predict the values exactly. For instance, heuristics and metaheuristics optimization algorithms are usually stochastic and therefore there is **no guarantee** that they eventually find a better solution than the current one. That said, the only thing that is guaranteed is that the solution value function of the job over time period is monotonically non-increasing. Empirically, the convergence of the solution value towards an optimal solution has hyperbolic shape. This assumption was made after the analysis of the runtime solution value data from optimization algorithms described in section 6.2. In addition, the script, which is able to visualize, the solution value function during the time was developed. This Python script is part of the implementation and can be found in the `scripts` folder inside the root of the project.

Moreover, it is not possible to use the time as x axis, because it would not be possible to extract information about how adding more available per-

formance will modify the predicted solution value function of the job. For that reason, it is better to use the number of iterations, that optimization algorithm performed, instead of time unit.

4.1.1 Hyperbola time series fitting

The generic equation for expressing hyperbola function on two dimensional graph is following.

$$a + \frac{b}{x + c} = y \tag{4.1}$$

Where a, b, c are parameters and x, y are axis values. For usage in computer algorithm, it is better to transform the equation into the form, where there is no division. Apart from the better performance in favor of multiplication [14], it is possible that the state when $x = -c$ occurs. If there is the division, the resulting value will be infinity, which breaks next algorithm iterations.

Instead, it is better to use following form, where there is no division and 0 as a result is not a problem for the following algorithm iterations.

$$ax + ac + b - yc = yx \tag{4.2}$$

Since the solution value prediction should be computed as fast as possible, it was decided to use mathematics optimization approach transforming the problem into non-linear least squares problem.

Non-linear least squares problems are often solved by the algorithms based on iterative estimate improvement. The example of this algorithms are the Gauss-Newton algorithm [15] and the Levenberg–Marquardt algorithm [16]. The second mentioned non-linear algorithm is more robust than the Gauss-Newton, because of the Marquardt parameter [16], which means that in many cases it finds a solution even if it starts very far off the final minimum.

Using Levenberg–Marquardt algorithm means, that it is necessary to know the derivation of the function, algorithm is trying to fit in. Derivation of the used function 4.2 is then following.

$$f'(x) = (c + x, 1, a - y) \tag{4.3}$$

As the target values, are used $x \cdot y$. As the parameters, that Levenberg–Marquardt algorithm is trying to fit in are used a, b, c.

4.2 Load balancing decisions

To make the most informed load balancing decisions while scheduling multiple optimization jobs, the application uses dynamic scheduling with centralized node running the load balancing algorithm.

The application also takes advantage of knowing the exact maximal time of an execution thanks to the input parameter D^j defined in section 3.1.1. Also, because of this parameter, it is possible to create scheduling decisions for much larger time horizon, because algorithm is aware of the future workload.

The definition formalized in section 3.1 implies that it is possible to use integer mixed integer linear programming solver, because the problem itself is defined as integer linear programming problem. That is indeed possible, but after careful consideration we rather decided to use heuristic approach. The main reason for selecting this type of optimization algorithm is, that it provides suitable results during the whole runtime. This could be very handy when the time for load balancing decisions is tight and in such case, the mixed integer linear programming solver would not have enough time to provide suitable solution, because the one, it provided, would not be optimal at all.

The optimization solver, which was chosen for the application, was previously mentioned (2.2.2) heuristics optimization engine OptaPlanner. Unlike TASP (2.2.2), the OptaPlanner is open sourced. The implementation based on OptaPlanner is described in section 5.4.

4.3 Complete application algorithm

The load balancing algorithm phases are divided into scheduling rounds. Each scheduling round produces new execution plan. The execution plan is created for specified scheduling horizon, this horizon is the period of time, which is limited by the time $t + 1$ and the t_{max}, which defines the end of the execution plan and where the t is the time of an execution. In other words, each scheduling round, executed in time t, produces the scheduling plan with scheduling horizon from $t + 1$ to t_{max}.

The scheduling horizon can be configured in the scheduling properties described in chapter 5. The length of scheduling window can be configured as well.

The following steps describes the way, how the load balancer works.

1. Poll jobs from the jobs queue.
   - The incoming jobs from API are stored in the queue, until the scheduling algorithm picks them up. That happens when the new scheduling round is engaged.
2. Analyze and filter jobs, that are not relevant for the current scheduling round.
   - Filtered out are the jobs, whose execution time exceeded the maximal possible execution time D^j or whose cost has exceeded the maximal cost P^j.
3. Convert received jobs into the inner data representation.
   - The scheduling core works with different data objects, than the load balancer API. For that reason, the data must be converted from the data transfer objects structure to the OptaPlanner domain representation.
4. Create predictions based on the solution value of the jobs and on the history of the load balancing decisions.
   - The process of making the predictions is described in section 4.1.
5. Produce execution plan using OptaPlanner scheduling.
   - The scheduling is limited to the amount of time defined as scheduling window. When the scheduling reaches the scheduling window (for example 60 seconds), it is stopped.
6. Convert created plan into time schedule and send them back to the client.
   - Transform internal domain representation into DTO layer and send them back to the client.
7. Engage the next scheduling round and go to the step 1.

Chapter 5

Implementation

In this chapter we would like to present the technologies that were used while implementing the previously described load balancer. During the development, base package of the application was named `OLB`, which is an acronym for **O**ptimization **L**oad **B**alancer. In the following pages, the developed application is called this way.

5.1 Architecture

Although this paper goals aim solely on the scheduler and introducing the new load balancing strategy, the architecture keeps in mind future work outlined in the section 7.1. Therefore the system's architecture is based on the idea of cooperating microservices, where each service has control over specific part of the infrastructure.

Microservice architecture is a software design architectural style that structures an application as a collection of loosely coupled services that are organized around the system's business capabilities [17] and are independently deployable with enabled continuous delivery [18]. Microservice architectural design also helps to the system's better horizontal scalability by using multiple instances of one microservice and the orchestration module.

5.1.1 Architecture scheme

Scheme 5.1 visualizes only system's core architecture. However, whole design keeps in mind future infrastructure development proposed in section 7.1. Implementation itself was developed accordingly and used technologies and techniques are described in following sections.

Core component, which is responsible for scheduling and load balancing, is composed of API, converter, predictions and scheduler module.

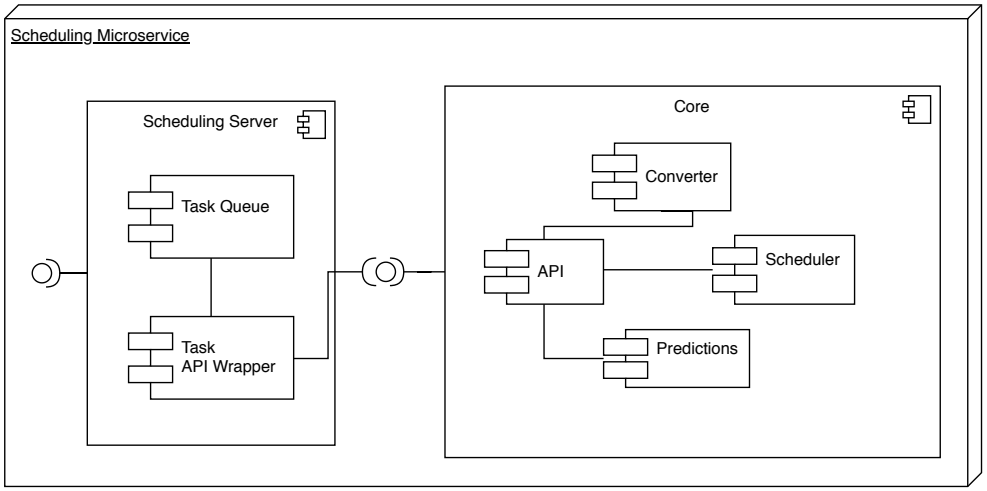

Figure 5.1: Microservice architecture with scheduling core

- *API module* implements common core interface `OlbCoreApi` and is responsible for scheduling requests handling. Actual implementation of API interface is class `OlbCoreApiImpl`.
- *Converter module* is used to convert received input data into inner scheduler data representation and then back to common data transfer objects. This converter is implemented as a class `InputToDomainConverter`.
- *Scheduler module* contains constraints, evaluator and scheduling system based on OptaPlanner solution (described in section 5.4). Scheduler module consist of multiple packages, `constraints` - containing all constrains for scheduling algorithm, `domain` with defined scheduling domain for OptaPlanner, `evaluation` which includes evaluator calculating planning score and `solver` package with factory initializing OptaPlanner scheduling core.

Scheduling server provides HTTP API access to the core and serves as microservice base. Server module is based on Ktor framework (described in section 5.2.4) that runs under the hood and provides HTTP functionality., The server API uses binary serialization and accepts data transfer objects used in the solutions. This is because of the number of interfaces and loosely coupled data objects, that are being used in the application.

Simulations architecture

Simulations module (project module `simulations`) is designed as another microservice to simulate future load balancing system's behavior. Following figure 5.2 shows architecture of the module.

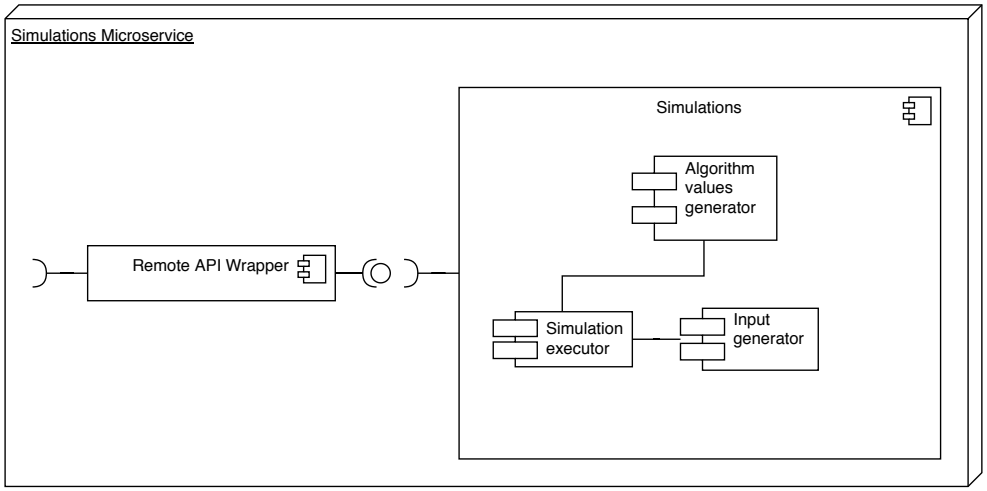

Figure 5.2: Simulations module scheme

Input data are generated by input generator module, which can be found for example in `DomainBuilder` class. Algorithm values are parsed from file in class `DataParser` and corresponding model is created on top of them in `JobWithHistoryFactory`.

Remote API wrapper is used to create connection between remote microservice, with scheduling API, and simulation. For the simulation module, the connection seems to be synchronous. This is because there is a blocking queue used to store and answer the calls between these two microservices. Thanks to this solution, simulations can be run in microservices mode as well as locally without any additional effort needed. Remote scheduling solution is implemented in project module `remote−scheduler`. Local simulations can be found for example in `OnePlanningRoundMain` or `ExecutionConfiguration` classes.

5.2 Development stack

The development stack is based on the Java platform, targeting primarily JVM 11[9] but including backwards compatibility with JVM 8. However, the traditional Java platform programming language Java was not used.

5.2.1 Programming Language

The OLB[10] is not bound to the single technology, which could limit the development stack, and for that reason, we had a free choice while making the

[9] Java Virtual Machine - runtime environment for Java byte code
[10] Optimization Load Balancer, name of the application

decision about the programming language used for the OLB implementation.

OLB is programmed in the programming language **Kotlin**. This cross-platform, statically typed, general-purpose programming language is developed by JetBrains [19]. Kotlin is 100% interoperable with Java because it uses JVM as its runtime and it is compiled to the Java Bytecode. Apart from the Java Bytecode, it can be also compiled to JavaScript or native code. [19] The main advantage of Kotlin is its strong and aggressive type inference, meaning that for the most of the time, it is not necessary to specify used data type since Kotlin compiler is able to infer it from the context. [19] It results to concise language syntax and therefore to the faster development in general.

Another great advantage is the Kotlin's *null safety*. Kotlin compiler distinguishes between non-nullable types and nullable types and enforces *null checks*[11] when the object has nullable data type. This feature effectively leads to less problems in the code and drastically reduces *Null Pointer Exceptions*[12] during the runtime.

5.2.2 Build environment

The application uses Gradle as its build automation system. It was chosen mainly because its incrementally build system, that works by tracking input and output of tasks, including files changes tracking, and only running tasks, that are necessary and thus reducing the time necessary to build the project. Also, it processes only these files, that were changed between tasks execution. Another reason we choose Gradle was, that it is preferred build system for Kotlin.

The preferred approach to build the application is to use Docker and build the application as the Docker image, which can be then run inside the Docker container.

Docker build environment

To keep build clean and reusable on almost every operating system and machine setup we decided to use **multistage Docker build**[13] which uses different base docker images for the build and for the run phase. Since OLB targets JVM 11 environment and uses Gradle as its build system, *gradle:5.4.0-jdk11-slim* is used as base image for build stage. This image contains all necessary Gradle build tools while having smaller size than common Gradle Docker image. Even smaller (in terms of size) are *alpine* based docker images. Alpine is smallest possible Linux core, which is widely used in the wide range of Docker base images. Alpine is focused on the smallest possible size of the

[11] Check whether the object being used has not null value

[12] Exception raised when code access reference that has null value

[13] Docker is a technology that performs operating-system-level virtualization, meaning that it uses hosts operating system kernel

image, while having all necessary tools build in. Unfortunately, there were (at the time of development) no official JVM 11 alpine images since there is no official stable OpenJDK[14] 11 build for Alpine Linux.

5.2.3 Runtime environment

The preferred runtime environment is a Docker system, where the application image runs inside the created docker container.

Docker runtime environment

The build application files are copied from the Docker build stage to the Docker runtime stage. As the runtime base image in multistage build was used *openjdk:11-jre-slim* image, because it is official OpenJDK 11 Docker image and therefore it is declared as stable.

Because there was used *gradle application plugin* while building the application, startup scripts were generated by the Gradle. These scripts are then used to start the application itself inside the Docker container.

When starting the whole application, multiple services must be started up. Therefore, because of the containerized environment, where containers can not access each other, multiple containers must be started and virtual network connecting them together must be created. This process can be automated using Docker Compose.

Docker Compose

Docker Compose [20] is an application for defining, running and managing multi-container Docker applications. It automatically creates Docker networks as well as Docker volumes. With writing down the definition of multiple Docker applications to the one Docker Compose configuration file, it is possible to create powerful micro services architecture, which can be build or started using single command.

Thanks to the created Docker networks, containers can communicate with each other using Docker Compose service names, therefore they do not need to know specific IP address they are running on.

Docker Compose is used in the implementation of OLB since it is designed with micro services architecture in mind. There are two services - Scheduling server and Scheduling client. Scheduling server provides ability to schedule process execution on the various computers and contains all core algorithms. Scheduling client is an example application which uses ability of scheduling server. There are implemented various simulations, which are being executed by scheduling client.

[14] Open-source implementation of the Java Platform, Standard Edition

5.2.4 Framework

Because of the overall micro services architecture of the project, some kind of web framework was needed. There are many Java based web frameworks, that could be used. We would like to present two of them - *Spring Boot*, which is traditional and widely used web framework for all kind of Java web applications and *Ktor* - relatively new, lightweight Kotlin framework build upon the Kotlin Coroutines[15].

Spring Boot

Spring Boot [21] is an open source Java Spring-powered web framework. It takes an opinionated view of the Spring platform, meaning that Spring Boot automatically configure Spring and 3rd party libraries whenever possible, and therefore enables usage of it to wider audience. It is highly dependent on the starter templates feature which provide pre-configured templates for various types of web applications. This for example allows user to start with already working we server and thus simplify the start of the application development [22]. Spring Boot contains comprehensive infrastructure support for developing enterprise monolith web applications as well as micro services [22].

Ktor

Ktor [23] is an open source web framework for building asynchronous servers and clients in connected systems such as web applications and http services. It designed for quickly building web applications with minimal effort and it doesn't impose a lot of technology constraints such as logging, persistent, serializing, dependency injection etc. [24] It is developed by the same company as Kotlin is, JetBrains.

The final decision was to use **Ktor** as the web framework, mainly because of its very light implementation and native Kotlin support. Also, for such project, the features of Spring would not be fully utilized and therefore the complexity of Spring could potentially slowed down the entire application.

Because Ktor by default does not contain any dependency injection framework, We decided to use lightweight DI[16] framework *Koin* [25]. This framework is written in Kotlin and have its own DSL[17] for the dependency specification, which is very handy for the medium sized project.

[15] Way of asynchronous or non-blocking programming that generalize subroutines for non-preemptive multitasking with using suspended/resumed task execution

[16] Dependency Injection

[17] Domain Specific Language

Route discovery library

The default way, how to create a HTTP endpoint (Ktor calls them *routes*), which can handle HTTP requests is registering it within the `Application` context. The `Application` context is accessible by its instance that is given to user when the Ktor is being started. This means that no *route* can be registered without using instance of `Application`.

During the development of the application and using Ktor framework, we decided that proprietary way of registering routes was not something we would like to be using, mainly because it did not allowed to have simple class serving only as a route without having to inject the *Application* instance. Also, since the routes must be registered during the application startup, using the new class for each route would mean to create instance of the class and executing the method to register the routes manually. Another reason we did not like the Ktor default approach was, that we prefer to inject class dependencies using the construct injection instead of using the setters injection.

- Constructor dependency injection - using constructor of the class to set all instances of the objects, that class uses. The main advantage is that the instance of class is always in a valid state, because it has all dependencies resolved during the instance creation.
- Setter dependency injection - the dependent objects are provided by the setter methods. This gives the freedom to manipulate the state of the dependency references at any time. However, it is possible to use the instance without setting the dependencies which could lead to the undefined behavior or to the *Null Pointer Exceptions*

To solve this `Application` instance dependency and to enable constructor dependency injection approach, we decided to implement simple library which would solve this issue for us. We came up with different way how to register various types of application's routes using the annotations, reflection and dependency injection strategy.

Preconditions for successful usage of the library are following:

- *Koin* [25] - dependency injection framework which is used for resolving dependencies needed in the routes
- *Reflection library* [26] - library used for runtime lookup for classes with specific annotation
- Using the `@Route` annotation on the class that is meant to be route, the class has to also inherit from `RouteBase`
- Registering all necessary routes dependencies in *Koin* modules during the application startup

- Provide base package name where routes are placed.

Following algorithm is used to find and register all routes used in the project.

Input: Package name, where all routes are stored
routes ← find all classes annotated as `@Route` in provided package name;
for ***route*** *in* ***routes*** **do**
  dependencies ← obtain dependencies needed for creating instance of **route**;
  routeInstance ← create instance of **route** using **dependencies**;
  register **routeInstance** in instance of `Application` ;
end
Output: All routes are registered and ready to use

The implementation of the simple route is then following:

```
@Route
class HelloRoute(sr: Service) : RouteBase("hello") {
    init {
        route {
            get {
                call.respond(sr.sayHello())
            }
        }
    }
}
```

The route is automatically instantiated and registered by the Routes discovery library. The programmer does not need handle it by himself.

For the library startup we designed a builder class using fluent builder pattern `ApplicationDependencyBuilder`. Usage of this class can be found in the `ServerStarter.kt`.

5.3 Algorithms values prediction

The implementation of Levenberg–Marquardt algorithm is not the aim of this paper, for that reason the application uses Java compatible library, which contains implementation Levenberg–Marquardt algorithm and provides way, how to use it.

OLB uses two different libraries Apache Commons Mathematics Library [27] and Mathematical Finance Library [28]. The both libraries have custom wrapper which implements `HyperbolicRegression` abstract class and they can

be exchanged in the application when decided. The reason, there are two different implementations and two different libraries, is that their performance can differ in distinguish scenarios. By default, the Mathematical Finance Library is used, because it provides better results in runtime predictions[18]. The implementations can be found as `ApacheHyperbolicRegression` class for Apache Commons Mathematics Library and `FinMathRegression` class for Mathematical Finance Library.

5.4 Load balancing decisions with OptaPlanner

Scheduling system implementation uses OptaPlanner library core in version `7.19.0.Final` [29] and it is crucial part of the `core` module and application itself.

5.4.1 Formalized definition representation

In this section, the thesis describes mapping between formalized problem definition proposed in section 3.1 and actual implementation in the code.

Each job, which is indexed in definition as j, implements `Job` interface and the main implementation, used in the core while scheduling, is the `PlanningJob` class. Input variables D^j and P^j are then specified as a `JobParameters` property of the `Job` interface.

Resources r are implemented as a sealed class `Resources` composing of `CpuResources` and `MemoryResources`. Resources belong to resources pools, which can be imagined as a physical computers or a virtual machines. Resource pools then cary information about the cost ${}^{r}c$ of the underlying resources. The pools are represented as a `ResourcesPool` interface.

Class `JobValue` represents a solution value of the job during time v_t^j and can be found as a property in the interface `JobWithHistory`. A job, that has some historical information (like a solution value of the job during the time and the scheduling data). Solution value of the job related information uses `AssignmentsEvaluation` during scheduling to compute reward for scheduler with value S_t^j. Resources cost C_t^j value is used in the cost constraint `CostEvaluation` for comparison with P^j. In the similar constraint `TimeEvaluation`, t value is compared with D^j to check, whether all specified constraints are satisfied.

Scheduling output is always `AllocationPlan`. It contains job domain, resources domain, overall cost and created time schedule. From the latest, values T^j and C^j can be computed very easily, therefore are not present directly in interface as properties.

[18] There is a Python code, which can provide graphs from values predictions, please see `plot_predictions.py` and `pw.forst.olb.simulation.prediction` package.

5.4.2 Scheduling Algorithm

The OptaPlanner scheduling itself has two main phases. *Construction heuristics*, that tries to build initial solution in a finite length of time. This partial solution is not always feasible, but it is found in relatively short time and then it is passed to the next scheduling phase. *Local search* with metaheuristics that can enhance the partial solution found in previous phase.

OptaPlanner contains various types of construction heuristics (i.e. *first fit*, *weakest fit* and *strongest fit*) as well as local search metaheuristics such as *hill climbing*, *tabu search* and *simulated annealing*. As the best combination of construction heuristics and local search proved to be *first fit* with *tabu search*.

The First Fit algorithm cycles through all the planning entities, initializing one planning entity at a time. It assigns the planning entity to the best available planning value, taking the already initialized planning entities into account. It terminates when all entities have been initialized [30].

The Tabu Search metaheuristics search is based on local search optimization method and enhances it by worse step strategy, when at each step worsening moves can be accepted if no improving move is available. In addition, prohibitions are introduced to discourage the search from coming back to previously-visited solutions [31].

5.4.3 Implementation

The scheduling implementation can be found in module `core`. The constraints are placed in the package `pw.forst.olb.core.constraints`. OptaPlanner related implementation is placed inside the `pw.forst.olb.core.domain` package and the plan solution evaluator in `pw.forst.olb.core.evaluation` package.

All custom constraints should implement `CompletePlanEvaluation` or `PlanEvaluation` interface. That way, they can be used in custom score evaluator, which is then used to generate score of the given plan. The constrains are stored in collections of previously mentioned interfaces and evaluated at once, when plan is submitted. Thanks to this solution, additional constrains can be added or removed very easily.

As an input for the scheduling algorithm interface `SchedulingProperties` is used. This interface defines properties necessary for the scheduling infrastructure such as `maxTimePlanningSpend` which defines how long can the application run the scheduling or `cores`, describing how many cores in the computer can algorithm utilize by spawning scheduling threads.

The OptaPlanner scheduler instance is created by custom factory implementation `OptaPlannerSolverFactory` and uses base configuration defined in `solverConfiguration.xml` file.

Chapter 6

Experiments

In this chapter, we would like to present, how we tested the load balancer. The simulations were designed to reflect the real-life situations and to simulate the most common usage of the load balancer.

6.1 Simulations implementation

To test the load balancer, there are two modules, that contain simulation code used for testing - `simulation` and `remote−scheduler` module. The simulation engine and all simulation use cases are located in the simulation module. The second mentioned module contains server, which runs simulations on the remote API. This is especially useful when testing whole scheduling environment and it is as closest as possible to the real-life environment, which should be based on the microservices architecture.

6.2 Optimization algorithms data

For the proper testing environment, the real runtime data of the optimization algorithm were needed. We decided to use TASP (mentioned in subsection 2.2.2) as heuristic algorithm, which execution could be potentially scheduled by the instance of the optimization load balancer. We did not implement a new TASP instance, instead, we used an instances from Stochastic Dynamic Vehicle Routing Problem master's thesis by Petr Eichler [32].

These instances solve real life vehicle routing problem and mainly for that reason are ideal for the testing purposes. We slightly modified the code from the thesis for observation purposes and added the time measuring functionality, which tracked the time between the algorithm's iterations and the current solution value of the job in each iteration.

In overall, we executed and measured 56 different instances of TASP. The observations can be found in `jobs-data/input` folder inside the implementa-

tion project and they are being used in the simulations, where the simulation module randomly selects one file with runtime data for each job and assigns it to the job, that is being scheduled. The data are then effectively used as an input data for the load balancer.

6.3 Simulations

There are two main randomized simulation scenarios inside simulation module (module described in 5.1.1). Both simulation can be started up locally using `SimulationExecutor` or using `docker−compose` microservices runtime environment. Input data for tests are created randomly, based on number of scheduled jobs and given planning horizon (how much steps ahead should scheduler count with). The number of scheduled jobs can be easily edited directly in code. For first simulation data and input please refer to `OnePlanningRoundSimulation`, for second to `RuntimeSimulation`.

Simulation's output (produced solution) is printed to standard output. Data displayed in listing 6.1 are an output produced by simulation with 5 jobs being scheduled at once.

Listing 6.1: Simulation data output

```
                Times:||  0|  60|120|180|240|300|360|
———————————————————— ||——|———|———|———|———|———|———|
     Cost: 1 + 0.02||  2|   2|  4|  3|  3|  2|  2|
     Cost: 1 + 0.02||  2|   2|  4|  3|  3|  2|  2|
     Cost: 1 + 0.02||  2|   2|  4|  3|  3|  2|  2|
     Cost: 1 + 0.02||  3|   4|  4|  3|  3|  2|  2|
     Cost: 1 + 0.02||  4|   4|  4|  3|  3|  2|  2|

   Cost: 1.5 + 0.02||  1|   1|  1|  2|   |   |   |
   Cost: 1.5 + 0.02||  1|   1|  1|  2|   |   |   |

  Cost: 10.0 + 0.05||  0|   0|   |   |   |   |   |
  Cost: 10.0 + 0.05||  0|   0|   |   |   |   |   |

Total plan cost: CostImpl(value=321.08)$
```

`Times` axis shows time units (t value described in section 3.1) in seconds. Second, vertical axis, visualizes resources. Name, `Cost: 1 + 0.02` is name of the resources provider (explained in section 5.4.1), and each line is one usage unit - meaning that it could be one physical core or for example percentage of shared processor. In implementation, this value is referred as CPU core, but in fact, it is dimensionless value expressing usage of some system.

Each cell contains either number or is empty. Number is job ID and indicates, that this resource is allocated to job with displayed ID. This is effectively ${}^{r}x_{t}^{j}$ value explained in section 3.1.1.

Total plan cost is sum of all particular costs of all jobs - their resources allocations. Therefore this is the cost of created plan.

First simulation is designed to use only first scheduling stage described in section 4.3 and create static initial plan which is then not modified. This simulation is implemented in `OnePlanningRoundSimulation` class.

TODO - more information about simulations

Chapter 7

Conclusion

All goals of this thesis were fulfilled. This thesis analyzed the state-of-the-art solution for the load balancing systems in the section 2.1. It brought an overview of various optimization problems, techniques and algorithms that are being used to solve diverse problems in section 2.2.

The thesis described and formalized the problem of the load balancing of optimization algorithms in chapter 3. Solution of the formalized problem was then proposed in the chapter 4. The main goal of the thesis was then fulfilled in the following chapter 5, where the implementation of the new system was described. This implementation is attached to the thesis.

The solution with 6767 lines of Kotlin code[19] proved, that it is possible to use it as load balancing algorithm for optimization algorithms.

7.1 Future work

To achieve production ready load balancing system, an execution module, which would transform the created plan into physical actions such as running, stopping and moving the jobs between the physical execution nodes, is needed.

Infrastructure development

As soon as the previously mentioned execution module is implemented, the application can be deployed into real life environment. Proposition is to make optimization algorithms running as Docker containers and the execution module would operate with Docker machines, which would be running on the execution nodes. In this way, the assigned resources would be very easily changed on one execution node. Migration to the next execution node would not be problem as well, since the containers could be wrapped and transported through the network.

[19] Lines provided by `find . −name "*.kt"| xargs cat | wc −l` bash command in root folder of the project

Another infrastructure related feature is the full JSON-enabled REST API. Currently only binary serialization is supported. In the future, full REST with JSON as its transport format should be supported.

Routes discovery library

Routes discovery library was very handy during the development of application's server parts and we believe that this way of routes registration in Ktor would suit to many developers as well.

Therefore we would like to refactor it from the base project and create open source project which will ensure future library development. We would like to also make it more generic, because right know, it depends on specific Ktor and Koin version. Although Ktor dependency is necessary since it is library developed specifically for Ktor, Koin should be replaced by generic way, how to obtain dependencies for routes.

Extension functions

During the application development, we created and tested many Kotlin extension functions. In general, these functions are not domain specific and for that reason we decided that we will publish them as well as Routes discovery library. These extensions could be useful when starting new project, because they are able to perform many operations in the single line of Kotlin code.

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Appendix A

List of attachments

1. CD with implementation described in chapter 5