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ACADEMIEJAAR 2012 – 2013

A HEURISTIC APPROACH TO UNIVERSITY COURSE TIMETABLING

Masterproef voorgedragen tot het bekomen van de graad van

Master of Science in de

Toegepaste Economische Wetenschappen: Handelsingenieur

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onder leiding van

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PERMISSION

Ondergetekende verklaart dat de inhoud van deze masterproef mag geraadpleegd en/of gereproduceerd worden, mits bronvermelding.

Eline Verhees

I PREFACE

This dissertation is the end piece of my five-year study Commercial Engineering: Operational Management at the University of Ghent, Belgium.

It gave me the opportunity to dive into the world of complex optimization problems and the countless ways to solve them. A subject of study that remained rather abstract during my education, but that nevertheless always fascinated me. The timetabling problem in particular interested me as it affects every single student in a university, but is often taken for granted.

Special thanks goes to my promoter Broos Maenhout with whom I could always discuss the difficulties I encountered in an inspiring way. I would also like to thank Lieven Rigo for his useful tips on implementing source code, Willem Lenaerts for his attentive reading of my text, and finally my roommates for their love and support during the last intensive weeks.

Eline Verhees,
Gent, 17-12-2012

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III LIST OF USED ABBREVIATIONS

CH	Constructive Heuristic
COP	Combinatorial Optimisation Problem
CSP	Constraint Satisfaction Problem
EA	Evolutionary Algorithm
GDA	Great Deluge Algorithm
GA	Genetic Algorithm
HC	Hard Constraint
HCV	Hard Constraint Violation
HEA	Hybrid Evolutionary Algorithm
IH	Initialization Heuristic
ILS	Iterated Local Search
ITC	International Timetabling Competition
LDF	Largest Degree First
LS	Local Search
LSDF	Least Saturation Degree First
MR	Mutation Random
MRR	Mutation Rate Random
MRS	Mutation Rate Smart
MS	Mutation Smart
NLGDA	Non-Linear Great Deluge Algorithm
OFV	Objective Function Value
OR	Operations Research
PATAT	Practice And Theory of Automated Timetabling
RW	Roulette Wheel
SA	Simulated Annealing
SC	Soft Constraint
SCV	Soft Constraint Violation
TS	Tabu Search
UCT(P)	University Course Timetabling (Problem)
VND	Variable Neighborhood Descent

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EEN HEURISTISCHE BENADERING VAN HET UNIVERSITAIR LESSENROOSTERPROBLEEM

Abstract

Het universitair lessenroosterprobleem (ULP) is een combinatorisch optimalisatieprobleem waarbij een set lessen moet ingepland worden in tijdsloten en leslokalen. Hoewel een degelijk lessenrooster enorm belangrijk is voor het functioneren van een universiteit, haar studenten en lesgevers is er nog geen optimale oplossingstechniek gevonden. In deze thesis test ik een hybride meta-heuristische benadering aan de hand van de benchmark datasets van de *International Timetabling Competition 2003*. Het geteste algoritme is een combinatie van een aangepaste Great Deluge zoekmethode en een incrementeel genetisch algoritme.

I. INTRODUCTIE

Sinds ongeveer vijftig jaar wordt er onderzoek gedaan naar een automatische aanpak voor het opstellen van een universitair lessenrooster. Voordien werd dit handmatig gedaan wat zeer veel man-werkdagen in beslag nam en bovendien tot sterk inferieure lessenroosters leidde vergeleken met een automatische aanpak. Een degelijk lessenrooster beïnvloedt in sterke mate het reilen en zeilen van een universiteit, de dagelijkse indeling van het leven van de studenten, en van dat van de lesgevers.

Mede door het steeds groter worden van universiteiten, door de uitbreiding van het lessenpakket, en door de steeds vaker toegekende mogelijkheid aan studenten om hun curriculum zelf samen te stellen, is een automatische aanpak van het lessenroosterprobleem onmisbaar geworden. In de volgende sectie geef ik een beknopte beschrijving van het algemene lessenroosterprobleem en van het specifieke probleem waarvoor ik een algoritme ontwikkeld heb. De sectie daarna geeft een kort overzicht van de literatuur omtrent bestaande oplossingsmethodes. Vervolgens beschrijf ik het gebruikte algoritme, en tenslotte geef ik de resultaten weer en de daarop gebaseerde conclusie.

II. HET PROBLEEM

Het universitair lessenroosterprobleem maakt deel uit van de grotere familie van *timetabling and scheduling problems*. Roosters voor een middelbare school of een universitaire examenregeling, alsook bijvoorbeeld de planning van arbeiders in een shiftensysteem zijn in deze familie terug te vinden. Uiteindelijk komt elke ULP neer op het volgende:

Maak een combinatie van de volgende elementen:

- Een set van **lessen C = {c_1, $c_{2,}$…, c_n}** met n het totaal aantal lessen.
- Een set van **lesgevers P = {p_1, $p_{2,}$ …, p_m}** met m het totaal aantal lesgevers.
- Een set van **lokalen R = {r_1, $r_{2,}$ …, r_k}** met k het totaal aantal lokalen.
- Een set van **tijdsloten T = {t_1, $t_{2,}$ …, t_h}** met h het totaal aantal tijdsloten.

op een dusdanige manier dat elke les C een lesgever P, een lokaal R en een tijdsslot T heeft toegewezen gekregen: C(P,R,T). Dit probleem kan worden uitgebreid met sets van eigenschappen van lokalen, sets van curricula, of kan worden gereduceerd door de toewijzing van lesgevers bijvoorbeeld niet in te vullen.

International Timetabling Competition 2003
Het probleem dat ik in deze thesis aanpak was het onderwerp van een internationale competitie in 2003. De exacte probleemstelling en alle andere benodigde data kan gevonden worden op volgende website: http://www.idsia.ch/Files/ttcomp2002/oldindex.html
Twintig test instanties worden voorzien waarbij lessen moeten worden ingepland in een weekschema van 45 tijdsloten en een bepaald aantal lokalen. Elk lokaal heeft bepaalde eigenschappen en elke les vereist gepland te worden in een lokaal met de juiste eigenschappen. Het rooster is *feasible* als aan volgende *hard constraints* voldaan wordt:

- **HC 1**: geen enkele student heeft meer van één les op hetzelfde moment.
- **HC 2**: het lokaal is groot genoeg om alle studenten van de geplande les een plaats te geven en beschikt over de eigenschappen die vereist zijn door de les.
- **HC 3**: slecht een les is gepland per lokaal per tijdslot.

Vervolgens wordt een kost aangerekend per verbreking van de volgende *soft constraints*:

- **SC 1**: een student heeft een les in het laatste tijdslot van de dag.
- **SC 2**: een student heeft meer dan twee opeenvolgende lessen.
- **SC 3**: een student heeft slecht één les per dag.

Dit probleem was het onderwerp van de ITC 2003. In 2007 en 2012 zijn er vergelijkbare competities georganiseerd waarbij het bestudeerde probleem telkens meer elementen van een realistisch lessenroosterprobleem kreeg. De datasets van van de ITC 2003 worden sindsdien veelvuldig als *benchmark* dataset gebruikt.

III. LITERATUUR

Er bestaan zeer veel methodes om het ULP aan te pakken. Een vaak aangehaalde onderverdeling van deze methodes is de volgende: (1) *sequential methods* (2) *cluster methods* (3) *constraint-based methods* en tenslotte (4) metaheuristieken. Ik zal hier enkel kort (1) en (4) bespreken. Voor een volledige overzicht verwijs ik naar Burke en Petrovic (2002).

(1) Sequential methods
Hierbij worden de lessen in een bepaalde volgorde gezet alvorens ze in te plannen. Deze volgorde wordt meestal bepaald op basis van de moeilijkheid van een bepaald event om het in te plannen. Deze ‘moeilijkheid’ kan berekend worden aan de hand van verschillende criteria. *Sequencing* wordt nog steeds veelvuldig gebruikt, maar meestal als onderdeel van een initialisatie heuristiek. Namelijk om een eerste maal het tijdsschema

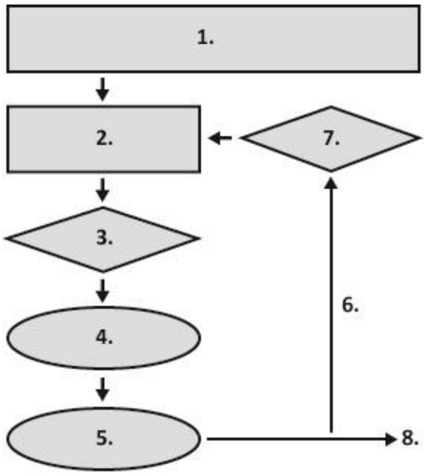
in te vullen. Voorbeelden worden gevonden in: Carter (1986), Burke (1998), Obit & Landa-Silva (2011), Abdullah et al (2010), Kostuch, 2005.

(4) Metaheuristieken
Deze categorie van methodes is ongetwijfeld de breedste en meest onderzochte. Een metaheuristiek wordt niet ontwikkeld per specifiek probleem, maar is toepasbaar op vele complexe problemen, en volgt meestal een logica waarvan men tot op de dag van vandaag nog steeds niet helemaal zeker van is hoe en waarom die soms wel en soms niet werkt. De vijf belangrijkste metaheuristische paradigma's zijn (met vermelding van auteurs die ze hebben toegepast op het ULP): Genetische Algoritmes (Erben en Keppler, 1996; Lewis en Paechter, 2004), *Ant Colony Optimization* (Socha et al., 2002; Malim et al., 2006), *Tabu Search* (Burke et al., 2004; Di Gaspero en Schaerf, 2001), *Simulated Annealing* (Kostuch, 2005), *Iterated Local Search* (Socha et al., 2002; Abdullah, 2007). Naast deze vijf bestaan er nog andere metaheuristieken, of variaties op de voorgaande. Vooral methodes die heuristieken en/of metaheuristieken combineren, ook wel hybride algoritmes genoemd worden het laatste decennium onderzocht en lijken de beste resultaten te geven.

IV. HET ALGORITME

De aanpak die ik gevolgd heb bestaat uit twee fases. In de eerste fase (1) wordt een *feasible* lessenrooster gecreëerd. Ik heb hiervoor drie Initialisatie Heuristieken ontwikkeld, waarvan de derde de best performerende bleek te zijn. Deze plant lessen in het rooster volgens een bepaalde volgorde. Het is dus een *sequential method.* Per les wordt het aantal plaatsten (zijnde een combinatie van een lokaal en een tijdslot) waar die les mogelijk kan gepland worden onthouden. De lessen met de minst mogelijke plaatsen worden dan eerst ingepland. De heuristiek is dynamisch aangezien bij elke les die geplaatst wordt, het aantal overgebleven plaatsen voor de andere lessen herrekend wordt. Het grote voordeel van deze heuristiek is dat hij onmiddellijk *feasible* roosters creëert, en dat voor elk van de twintig instanties van de competitie.

In fase twee wordt het lessenrooster geoptimaliseerd door het aantal schendingen van de *soft constraints* te verminderen. Dit gebeurt aan de hand van een hybride algoritme, namelijk een genetisch algoritme met een steady-state populatie (2) die wordt bewerkt door een van twee mutaties (4) en een lokale zoekmethode (5).



Hybride Evolutionair Algoritme

De lokale zoekmethode is een niet-lineair Great Deluge algoritme (vooreerst voorgesteld door Dueck, 1993, en aangepast door Obit en Landa-Silva, 2008). Per rondgang wordt op basis van een Roulette Wheel selectie (3) één rooster geselecteerd en vervolgens bewerkt door (4) en (5) . Als het bekomen rooster beter is dan het zwakste rooster in de populatie dan vervangt het deze laatste, tenzij het bekomen rooster meer dan 350 identieke allocaties heeft in vergelijking met een rooster in de populatie, dan wordt het beste van deze twee geselecteerd (6) en (7). Indien het gevonden rooster niet aan de populatie wordt toegevoegd wordt het verwijderd (8). De ene mutatie selecteert tussen nul en een bepaald random aantal (maximum begrensd door de *mutation rate)* van alle lessen en verplaatst die lessen naar lege tijdsloten, of verwisselt ze met een andere les. De tweede mutatie selecteert tussen nul en een bepaald aantal tijdslots (wederom begrensd door een *mutation rate*), die een hoger dan gemiddelde *soft constraint* kost hebben en verplaatst de events in deze tijdsloten naar beschikbare plaatsen. Bij beide mutaties wordt steeds *feasibility* behouden. De zoekmethode werkt met vier *neighborhoods:* N_1 verplaats een random event naar een lege plaats, N_2 verplaats een random event dat een *soft constraint* schendt naar een lege plaats , N_3 verwisselt twee events, en N_4 verplaatst een event uit één van de vijf tijdsloten die op het einde van de dag vallen naar een andere plaats, niet op het einde van een dag. Bij elke neighborhood wordt steeds gezorgd dat *feasibility* behouden wordt.

V. RESULTATEN

Het algortime behaalt goede resultaten voor elk van de twintig datasets van de competitie, die de resultaten van de algoritmes die achtste (Montemanni R., 2003) en negende (Müller T., 2003) eindigden in de competitie soms verbeteren, soms benaderen. De tabel op pagina 66 toont mijn resultaten naast de andere resultaten. Het nummer in de eerste rij geeft de officiële ranking van de uiteindelijke algoritmes weer. De waardes waarvoor mijn algoritme beter scoorde zijn aangeduid in vet.

VI. CONCLUSIE EN RICHTLIJNEN VOOR VERDER ONDERZOEK

De belangrijkste bevindingen van mijn methode is de toevoeging van *Neighborhood* 5. Deze methode is nog niet uitgebreid gebruikt en getest in de literatuur. Uit mijn resultaten blijkt dat het een zeer krachtige *neighborhood* is die de *Objective Function Value* van dit specifieke probleem sterk kan verbeteren. Verder bevestigt mijn algoritme dat hybride methodes zeer goede resultaten kunnen opleveren. Voor verder onderzoek raad ik aan *neighborhood 5* uitgebreider te testen en toe te passen in andere algoritmes, zoals bijvoorbeeld *Very Large Neighborhood Search of Variable Neighborhood Search*, maar uiteraard kan ze in elke lokale zoekmethode geïmplementeerd worden.

1. INTRODUCTION

This thesis is a study of the process of automated timetabling and automated university course timetabling in particular. Two respected researchers in this subject of study once said: *"Everyone has a story to tell about a timetable"* (Burke and Ross, 1995, p. 9). And that is indeed true. Timetables are indispensable in our modern society.

A good university timetable affects the life of students and teachers, as well as the quality of education at the university. It is thus crucial for every university, small or big, to develop a qualitative, balanced timetable. This is however no easy task. Even for relatively small universities the problem has such an amount of variables, restrictions and preferences of students and teachers that the complexity quickly increases. So, an automated approach emerges. It leads to substantially better timetables compared to those made manually, and it significantly alleviates the work of the university's administration.

Research towards automation of timetabling has been conducted for several decades now, but an optimal approach is still not found. In this light I attempted to develop an approach of my own and I hope that my research and results can contribute to the on-going optimization of methods to construct good, qualitative timetables. To find directions for my algorithm I studied the literature, the winning submissions of two timetabling competitions and other papers that could lead me towards interesting or promising methods.

The structure of this work is as follows: first I explain the importance of timetabling in general. Next I give a framework of the university course timetabling and explain the problem and its variants in detail. Thereafter the focus turns towards the International Timetabling Competition. This competition is held every five years since 2003 and its subject has been widely used as a benchmark problem by many researchers. The problem of the International Timetabling Competition of 2003 is the problem for which also I attempted to develop an algorithm. After I explain the competition, I give an overview of the literature and the existing methods to solve the university course timetabling problem. In the next two sections I extensively explain the algorithm I developed, how I came to this result, and the experimental testing of the parameters. In conclusion, I present my results and compare them with the official results of the aforementioned competition. Lastly, I state my conclusion, and suggest a possible direction for future research.

2. THE IMPORTANCE OF TIMETABLING

A ***timetable*** *is a plan of times at which certain events are scheduled to take place.*

Timetabling *is the action of placing events in a timetable.*

Oxford Dictionary

Timetabling has long been recognized to be a very difficult problem. Timetables are used in an extremely wide range of real-world situations. To name a few: hospitals, police departments, factories, schools, airports, railways… It is obvious that timetables are essential to make our community, our industries, and our daily life run smoothly. Without it employees wouldn't know when to come to work, airplanes wouldn't know when to take of, or policemen wouldn't know when to patrol their neighborhood.

Generating **a university course timetable** is a very complex and time-consuming task every university has to deal with, whether or not it is every year, or every semester. The complexity of this task comes from the wide variety of courses most universities offer. These courses have to be timetabled, while taking into account the preferences and skills of teachers, the choices of students, the availability and suitability of classrooms, the educational policy of the university, the offered expectations of courses, available budgets, …

However complex this task may be, it is absolutely necessary that every university, faculty or department comes up with **a feasible timetable**. A timetable is feasible when it can be effectively executed and when it meets the proposed requirements. This means that *every course has to be scheduled within a timeslot, located to a suitable classroom and assigned to a skilled teacher so that every student who registered for a course has the ability to attend the lectures.* Without a feasible timetable not one university would succeed in its goals.

The importance of timetabling goes beyond this, as it is not only our goal to construct feasible timetables, but to construct one which is as best as possible. Indeed, we try to **optimize the timetables**, considering students' and teachers' preferences and educational quality. An optimal timetable can make a big difference in a student's or a teacher's university life.

The previous paragraphs discuss the importance of timetabling in general. A more profound understanding of the importance of university course timetabling can be reached by looking at the different persons or groups who, on the one hand influence the construction of the university course timetable, and on the other hand are equally affected by it. We call these persons or groups the **stakeholders of the timetable**:

-The students: When thinking of a course timetable, the first thing that usually comes to mind are the students. Students and the complete student body are the main influences on the construction of the timetable. A course only has to be scheduled because of the simple fact that one or more students chose to enrol themselves in this particular course. If not, the course would not have to be scheduled. Another influence is the absolute size of the student body. The number of students who enrol in a particular course, greatly influence the requirements that have to be met when scheduling this course. More students in one course ask for a bigger classroom, or for a split of the course into more groups, which in turn asks for more teaching hours and more classroom space, …

Another factor is the fact that students enrol in several different courses to form their curriculum, which is a set of courses. Courses that are part of the same curriculum should not overlap. Originally universities would compose different curricula and students could choose one of them. However, lately there has been a trend of *modularization* which gives students the chance to compose their own curriculum. Of course this trend makes it a lot more difficult to fulfil the requirement that courses in the same curriculum shouldn't overlap. This issue poses the choice of *curriculum-based timetabling* or *student enrolment-based timetabling* (see infra p.9).

This also brings us to the ways students are affected by the timetable. When a student is enrolled in two courses that have an overlap in the timetable, he or she will have to find a solution. This can be dropping one of the courses or switching the followed lecture from week to week.

The last and least important way in which a timetable affects the student is the way in which it complies with the student's preferences. One might prefer not to have class on Friday afternoon or not to have class five hours in a row, but if the timetable is scheduled like this, he or she will have no choice but to obey the schedule.

-The teachers: This group influences the construction of the timetable by the contractual agreements it has with the university. When the contract of a teacher stipulates that he or she does not work on Wednesdays, the course that is taught by this teacher obviously cannot be scheduled on a Wednesday. Although the physical requirements that are needed from a classroom are determined by the intrinsic nature of the scheduled course and the size of the student body, as well as by the teachers demands, I will mention it under this paragraph. When a teacher, the number of students or a course itself requires the classroom to have certain physical elements, such as a laboratory or a slide-projector, this of course influences the scheduling of the course.

The timetable affects teachers in the same way it affects students, namely that they will have to plan their professional life as foreseen by the timetable. One difference of course is the fact that a teacher cannot have two or more courses at the same time as he or she cannot teach in different locations in one moment.

-The administration: The university's educational policy, stipulated by the administration, can influence the timetable in many ways. The administration can implement quality standards such as 'lectures cannot be attended by more than forty students at a time', or 'students and teachers should have a long break at least every three hours', or 'a classroom should be cleaned after every lecture' … In short, this group decides which minimum standards and requirements a timetable should satisfy.

The construction of the timetable is also influenced by the cooperation between the departments/faculties. The university can choose to have a centralized process of timetabling or a decentralized process of timetabling. The latter will be strongly influenced by the degree of cooperation between the different administrations, e.g.: one department can choose to make free classrooms available to other departments.

It is now obvious that timetabling is a very complex task, influenced by many entities and decision variables and affecting numerous stakeholders. In many universities this task is still done by hand, using timetables of previous years and making small adjustments to them. This requires many person-days of work and the solutions may be disappointing with respect to the different stakeholders (Schaerf, 1999). Given the complexity of this task and given the fact that many universities have to cope with a growth of their student body and with the trend of modularization, it is not difficult to understand that an automated approach to timetabling is very desirable. This is why there has been extensive research in this area for more than forty years. Overviews of previous methods can be found in the following surveys (Burke et al. 1997; Burke and Petrovic 2002; Lewis 2008).

2.1 CURRENT RESEARCH & ORGANISATIONS

Since 1995 eight international conferences have been held on the Practice And Theory of Automated Timetabling (PATAT)[1]. In 1996 a working group to complement these conferences was set up, the EURO Working group on Automated Timetabling (WATT)[2]. The PATAT conference is now held every two years and a WATT Workshop is held in alternate years as a special session of the conferences. In 2003 and 2007 an international timetabling competition (ITC) has been held with a price of 500 pounds and a ticket to the PATAT conference for the winning entry. These competitions were held on the subject of University Course Timetabling (UCT) in 2003[3] and Examination Timetabling as well as UCT, both curriculum-based and post-enrolment based timetabling in 2007[4]. In 2012 a new competition took place on the problem of high school timetabling.[5] Apart from these organisations many operations researchers and practitioners around the world study the problem and try to improve the current automated solution approaches (See section 6 p.21-27).

[1] http://www.asap.cs.nott.ac.uk/patat/patat-index.shtml
[2] http://www.asap.cs.nott.ac.uk/watt/index.shtml
[3] http://www.idsia.ch/Files/ttcomp2002
[4] http://www.cs.qub.ac.uk/itc2007
[5] http://www.utwente.nl/ctit/itc2011

3. GENERAL FRAMEWORK OF UNIVERSITY COURSE TIMETABLING

The previous section stressed the importance of timetabling and gave an introductory description of the actual problem. This section will provide a more profound, technical description of timetabling and more specifically of university course timetabling.

3.1 WHAT IS TIMETABLING?

University course timetabling is part of the bigger family of classic timetabling and scheduling problems. The words schedule and timetable have slightly different meanings. Although a *timetable* shows when every event should take place, it does not always indicate allocation of resources. A *schedule* will normally contain all the special and time-based information necessary for a process to be carried out. Thus, a schedule generally includes timeslots for every activity, assignments of resources and work plans for personnel or machines. However, the use of these terms as if they were synonymous is generally accepted in the literature (Müller, 2005).

A. Wren defines timetabling as follows:
"Timetabling is the allocation, subject to *constraints*, of given *resources* to *objects* (events, courses, personnel) being placed in *space-time*, in such a way as to satisfy as nearly as possible a *set of desirable objectives*." (Wren, 1996, p. 3)

Timetabling arises in a very wide range of application domains, such as in education (scheduling courses and exams in schools and universities), sport (scheduling games and tournaments), health institutions (scheduling patients and personnel), transport (scheduling busses, trains and planes), and many others.

3.2 ACADEMIC TIMETABLING

Academic timetabling refers to all timetabling problems that arise in an educational context. In the literature many variations of the timetabling problem have been studied. They differ from each other according to their type of institution (school or university), the type of events to be planned (courses or exams) and the type of constraints. Schaerf (1999) classified these problems into three main classes:

“School timetabling: The weekly scheduling for all the classes of a school, avoiding teachers meeting two classes at the same time, and vice versa;

Course timetabling: The weekly scheduling for all the lectures of a set of university courses, minimizing the overlaps of lectures of courses having common students;

Examination timetabling: The scheduling for the exams of a set of university courses, avoiding overlap of exams of courses having common students, and spreading the exams for the students as much as possible.” (Schaerf, 1999, p. 2)

The main difference between school and course timetabling is that university courses can have students in common, while school classes are separated sets of students. If two or more courses have students in common, they should not be scheduled at the same period. Additionally, in universities a professor typically teaches only one subject, while school teachers usually teach more than one course. Also, in the university problem availability and suitability of rooms plays a significant role, whereas school classes often have their own classroom.

Examination timetabling is very similar to course timetabling. Some specific problems can even be expressed both as a course or as an examination timetabling problem. However, there are some widely-accepted differences. Examination timetabling has the following characteristics (which course timetabling has not):

- “There is only one exam for each subject.
- The conflict condition is strict. We can accept that a student is forced to skip a lecture due to overlapping, but not that a student skips an exam.
- The number of periods may vary, in contrast to course timetabling where it is fixed.
- There can be more than one exam per room.
- A certain exam can be spread over several rooms.” (Schaerf, 1999, p. 23-24)

These differences imply different constraints, which usually results in a less constrained problem when comparing the two. Consequently course timetabling is often considered tougher than examination timetabling (Kostuch, 2003).

Of course, the classification above is not strict. A specific problem of a school or university can have certain characteristics or requirements so that it falls between two classes. For example, a school can give much freedom to its students in choosing their sets of courses. This would make the problem similar to a course timetabling problem. But the problem would still not have the typical and difficult aspect of course timetabling where one course can be attended by more than two hundred students.

Also other classifications can be made. Burke and Petrovic (2002) suggest two main categories, namely course timetabling and examination timetabling problems. Carter and Laporte (1997) suggest a sub classification of the course timetabling problem, namely course scheduling, class-teacher timetabling, student scheduling, teacher assignment, and classroom assignment. Classifications can be made in many ways, but for me the one of Schaerf (1999) is the most clear and logical.

Apart from these classification it needs to be said that there are numerous timetabling problems in any class: "they differ from each other not only by the types of constraints which are to be taken into account, but also by the density (or the scarcity) of the constraints; two problems of the same "size", with the same types of constraints may be very different from each other if one has many tight constraints and the other has just a few. The solution methods may be quite different, so the problems should be considered as different." (de Werra, 1996, p.1)

In this work, I will focus on course timetabling, and I will use the term university course timetabling (UCT) to avoid any confusion.

3.2.1 CURRICULUM- / STUDENT ENROLMENT- BASED TIMETABLING

One important distinction to be made is whether you will base your timetabling on curricula or on student enrolments. Some universities choose to offer only certain curricula to their students. A curriculum is a predetermined set of courses to which students can subscribe. Most European universities work with curricula. In curriculum-based timetabling the objective is to schedule the courses in such a way that there are no conflicts between two or more courses of the same curriculum.

As opposed to curricula, universities can offer their students the choice of their own set of courses out of all courses the university offers. In this case the timetable is constructed after student enrolment, with the objective of trying to minimise the number of course conflicts among a possibly large number of enrolments. Two courses that are chosen by the same student shouldn't be scheduled at the same time. This distinction will result in different models with different constraints and objectives. In many real world situations, the construction of a timetable will actually involve a combination of pre-enrolment and post-enrolment features and information. For example, universities that offer curricula often also provide optional courses that students can freely choose as an extension of their curriculum. In case of curriculum-based timetabling this will again increase the number of conflicts between courses.

3.3 PROBLEM DEFINITION

Even though the UCT problem exists in many variations, every single problem boils down to this:

The goal is to combine the following elements

- A set of **courses C = { c_1, c_2, … c_n }** with n the numbers of courses
- A set of **teachers P = { p_1, p_2, … p_m }** with m the number of teachers
- A set of **rooms R = { r_1, r_2, … r_k }** with k the number of rooms
- A set of **timeslots T = { t_{11}, t_{12}, … t_{dh} }** with d the number of days and h the number of timeslots per day

in such a way that every course C has assigned to it a teacher P, a room R and a timeslot T: C(P, R, T). For example, course 5, taught by professor 2 in room 12 at timeslot 31 would be represented as 'c_5 (p_2, r_{12}, t_{31})'. This should result in a feasible timetable satisfying all the hard constraints and minimizing the violation of soft constraints.
Depending on the specific characteristics of the problem the model can be extended with sets of students, sets of features of the rooms, sets of courses or curricula; or it can be alleviated by dropping the assignment of teachers, etcetera.

Basically, every UCT problem is a **Combinatorial Optimization Problem** (COP) that is **constrained** and **NP-hard**. The following paragraphs will discuss these three characteristics.

3.3.1 COMBINATORIAL OPTIMIZATION PROBLEMS

"Operations Research (OR) is an interdisciplinary research area with links to Mathematics, Statistics, Engineering, Business, Economics and Computer Science. The goal of OR is to find solutions for real-world application problems. This is mostly done via the construction of a mathematical model, its analysis with the scientific tools of the aforementioned subjects and the retranslation of the findings back into real-world recommendations." (Kostuch, 2003, p. 5) The landscape and the applications of OR are extremely diverse. Ranging from problems with a low complexity, for which an optimal solution can be found with a simple linear model and relatively low computational effort, to problems with extremely high complexity, for which even the most sophisticated models need immense computational effort to find just one good solution, let alone an optimal one. This wide range of applications of course led to many subsets of OR-models, techniques and fields of research.

All these problems can be roughly divided into feasibility problems, where the goal is to find out whether a solution exists that can be effectively applied or executed, i.e. that is feasible; and optimality problems, where the goal is to find a feasible solution that has an optimal value for the chosen objective function. Next, optimality problems are divided into those that deal with continuous decision variables, and those that deal with discrete decision variables. The latter are the combinatorial optimization problems.

Some well-known examples from COP are integer programming, the travelling salesman problem, minimal spanning trees, shortest paths, graph colouring, job scheduling, and timetabling and scheduling …

So all combinatorial optimization problems have the goal of finding a solution which is a **combination of a set of discrete variables** that:

- respects all hard constraints
- minimizes/maximizes the value of the objective function

“The relation between the choices made in the discrete domain and the effects on the objective function value are usually complex and not easy to trace. The discrete domain itself is usually huge and very often curtailed by complicated restrictions. This means that COP’s are often very difficult to solve even when employing sophisticated algorithms and hardware.” (Kostuch, 2003, p. 6).

3.3.2 CONSTRAINTS

Real-world problems always require the solution to meet certain preferences. These are expressed by constraints. Constraints can be categorized in different ways. The distinction between hard and soft constraints for UCT problems can be found in the literature.

Hard constraints are usually constraints that cannot be violated physically. This includes events that cannot overlap in time, such as classes taught by the same professor or classes held in the same room. However, sometimes hard constraints can in fact be physically possible, but are seen by the university as too important to be violated. Therefore they are made hard. An example of this is a professor who doesn’t work on certain days according to his contract. Only solutions that satisfy all hard constraints are considered to be feasible.

Soft constraints are constraints that may be violated, although it would be better if they weren’t. Therefore a penalty is given to the objective function every time a soft constraint is violated. These penalties are proportional to the severity of violating the constraint. Soft constraints are often those problems that are inevitably violated, meaning that if all these constraints were hard, it would be impossible to find a feasible solution. An example of a soft constraint is a professor that prefers not to work on Monday afternoon or no students having more than two consecutive courses.

Another interesting classification specific for the UCT problem has been made by Corne, Ross and Fang (1995). They divided constraints into five categories:

- **"Unary constraints:** these constraints consider only one event. E.g.: 'course *a* cannot be scheduled on Fridays' or 'course *b* has to be scheduled in room *c*'.
- **Binary constraints:** these are pairs of constraints, such as 'course *a* has to be scheduled before course *b*'. Also *event clash constraints* belong in this category, such as 'course *a* cannot be scheduled in the same timeslot as course *b*'. These constraints are applicable in almost every university. Also chains of binary constraints can be applied, such as 'course *a* has to be scheduled before course *b*, which has to be scheduled before course *c'*.
- **Capacity constraints:** these constraints consider the capacity of classrooms. E.g.: 'all events have to be scheduled in classrooms with sufficient capacity'. Also constraints about other features of rooms belong in this category
- **Event spread constraints:** these constraints consider spreading out events in order to reduce students' or teachers' workload, or aggregating events to comply with university policy. Also spreading of events in space is considered here, this can be important when students or teachers have consecutive events in different classrooms; they need sufficient time to move from one room to another.
- **Agent constraints:** these constraints concern the demands and preferences of all people directly influenced by the timetable: teachers and students.
  E.g.: 'Professor *x* prefers to teach course *a* on a Wednesday afternoon'." (Corne, Ross and Fang, 1995, p. 226)

Other classifications can be found in the literature. These can be useful to discuss different kinds and types of constraints, but it is equally important to realize that almost every real-world problem is different and will therefore have different constraints. Depending on the density and variety of the constraints problems will vary widely in complexity.

3.3.3 NP-HARD PROBLEMS

Every problem has a certain level of complexity, meaning that it differs in how hard it is to be solved. To formalize the notion of hardness the complexity theory has been developed. In this theory the complexity of a problem is expressed as the complexity of the best possible algorithm for that problem. This is usually expressed in the time it takes an algorithm to find a solution. The basis of complexity theory is the realization that as the input size *n* of a problem increases the time to find the optimal solution increases as well.

The class of P (polynomial) problems can be solved optimally in polynomial time. The growth in time demand for finding an optimal solution is bounded by a polynomial expression in *n*.

For the class of NP (non-deterministic polynomial) problems a solution can be *verified* in polynomial time by using a non-deterministic algorithm. However, when a currently known algorithm is applied to an NP problem, the time to *find* a solution increases exponentially with the input size n. This means that the problem cannot be solved in a deterministic way in a realistic and acceptable timespan, as the time required to solve an even moderately sized problem increases extremely fast. Therefore non-deterministic algorithms are usually applied to these problems, but unfortunately it is not possible to know whether the solution found by the non-deterministic algorithm is optimal.

The class of NP-complete problems is a subset of the NP problems and can be seen as the 'hardest' NP problems.

Complexity theory usually deals with decision problems instead of optimization problems. However by asking whether a certain problem is solvable for a specified objective function value, the two can be easily translated into each other. An optimization problem stemming from an NP-complete decision problem is called NP-hard.

The university course timetabling problem is an NP-hard problem. This means that a non-deterministic algorithm will be needed to solve it to a predetermined 'optimal' value.

4. METHODOLOGY

The reader should now have a clear understanding of timetabling in general and academic timetabling in specific as I discussed the basic variables and characteristics of the problem. In the next section I will discuss the ITC of 2003 and 2007 more profoundly. Next I will give an overview of existing methods and look at successful solution approaches to find directions for my own approach. Thereafter I will tackle the problem of the ITC of 2003 by developing my own algorithm. The two problems of the ITC are more or less similar, except for the fact that the 2007 problem is slightly more constrained and therefore more complicated. The reason for selecting the problem of the 2003 competition is twofold. First, the fact that these problems were subject of an international competition gives me the ability to benchmark my solution against other entries. Moreover, these two problems were specifically designed to be appropriate for algorithm performance testing whilst staying relatively close to real-world problems. Second, I will tackle the 2003 problem instead of 2007 because my ambition is not to find a solution for the most complicated, real-world simulating problem, but to be creative in developing my own algorithm. So to clarify, the goal of this dissertation is to develop a new algorithm for the problem of the ITC of 2003, which is a post-enrolment based university course timetabling problem.

When I say ‘develop a *new* algorithm’, of course I do not mean develop a completely radically new algorithm. Rather I will try to use different parts of existing algorithms and combine them in a way that they haven’t been combined before. This will lead to a new algorithm, a new sequence of steps that leads to a feasible and hopefully good timetable. As it is very difficult or almost impossible to predict the performance of an algorithm I will not predefine certain objectives, such as the desire to find an optimal timetable for the instances of the competition. Rather, my goal is to develop the algorithm and analyse the results in a way that might be useful for future research.

All the data I will use for my experiments will come directly from the ITC competition. PATAT provides twenty different sets of test instances, and every set consists of instances with variable complexity. This will give me enough data to test my algorithm profoundly.

5. INTERNATIONAL TIMETABLING COMPETITION

In this section I will describe the timetabling competitions of 2002 and 2007. First the organising institutions are introduced. Next I explain the two problems and the competition rules in detail. Finally I will shortly mention the winning papers. I incorporate the problem of 2007 so that the difference with the problem of 2003 can be seen. This shows the directions where research in this subject is going.

5.1 INTERNATIONAL TIMETABLING COMPETITION

The international timetabling competition has been brought to life by the EURO Working Group on Automated Timetabling (EWG WATT) and the Practice and Theory of Automated Timetabling (PATAT).

The **EWG WATT** is a working group of EURO, the Association of European Operational Research societies. EURO is a non-profit organisation with the aim of promoting operational research throughout Europe. Within the EURO network there are many working groups that specialize in specific operations research topics. These are small groups of researchers for which EURO provides an organisational framework. WATT is one of these groups. The researchers meet at least once a year, give sessions in conferences, publish articles in journals, and organise conferences themselves. In this way the working group provides a contact forum where members can exchange ideas, experiences and research results, and support each other in their work. WATT organizes a workshop every two years.

PATAT is an international series of conferences on the practice and theory of automated timetabling held bi-annually as a forum for both researchers and practitioners of timetabling to exchange ideas. The steering committee of the PATAT conferences consists of researchers from universities around the world, many of whom are also member of the EWG WATT.

For the first time in 2002 these two organizations decided to start up a competition for automated timetabling. The overall aim was to create better understanding between researchers and practitioners by allowing emerging techniques to be trialed and tested on real-world models of timetabling problems. Also, the organizers hoped that conclusions of the competition would further **stimulate debate and research** in the field of timetabling and that the competition would establish a widely accepted **benchmark problem** for the timetabling community. This goal has definitely been achieved as the data sets of the competition are used frequently in many papers published during the last decade.

5.2 2003 COMPETITION[1]

In 2003 the Metaheuristics Network was also one of the organizers of the competition. The Metaheuristics Network[2] was a project sponsored by the 'Improving Human Potential**'** program of the European Community. The activities of the Metaheuristics Network, coordinated by Prof. Marco Dorigo, started in September 2000 and were accomplished in August 2004.

To stimulate participation in the competition a prize of € 300 and a ticket to the 2004 PATAT Conference was administered to the winner.

5.2.1 THE MODEL

The model used is a reduction of a real-world timetabling problem encountered at Napier University, Edinburgh, UK. The problem consists of a set of *n* events E = {e_1, …, e_n} to be scheduled in a set of 45 timeslots T = {t_1, …, t_{45}} (5 days in a week, 9 timeslots in a day), and a set of j rooms R = {r_1, …, r_j} in which events can take place. Additionally, there is a set of students S who attend the events, and a set of features F provided by the rooms and required by the events. Each room has a size and each student attends a number of events. The model is thus post-enrolment based and not curriculum-based. The following information comes directly from the competition's website:

"A feasible timetable is one in which all events have been assigned a timeslot and a room so that the following **hard constraints** (HC) are satisfied:

- no student attends more than one event at the same time (HC1);
- the room is big enough for all the attending students and satisfies all the features required by the event (HC2);
- only one event takes place in each room at any timeslot (HC3).

[1] All information can be found on: www.idsia.ch/Files/ttcomp2002

[2] http://www.metaheuristics.net/index.php?main=1

In addition, a candidate timetable is penalized equally for each occurrence of the following **soft constraint** (SC) violations:

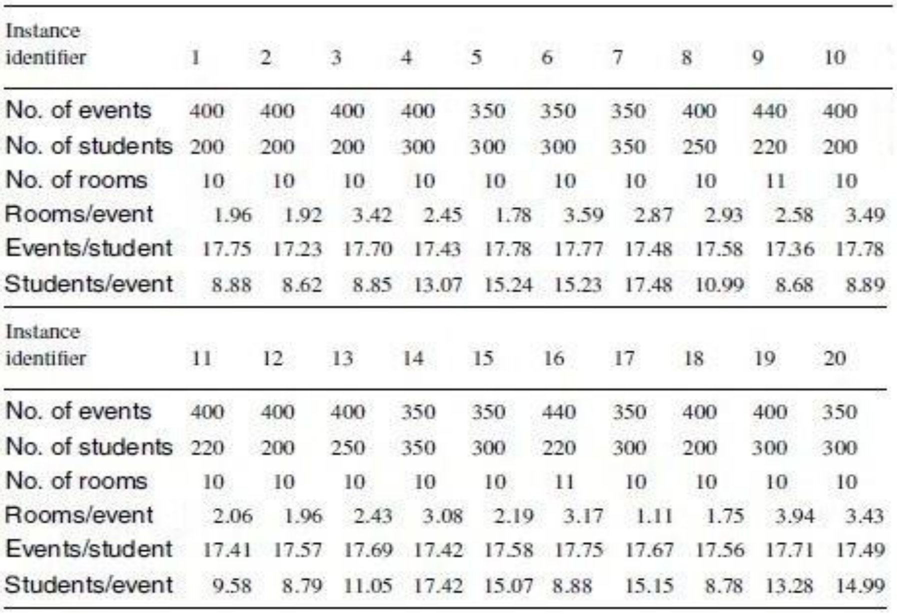
- a student has a class in the last slot of the day (SC1);
- a student has more than two classes consecutively (SC2);
- a student has a single class on a day (SC3).

Infeasible timetables are worthless and are considered equally bad regardless of the actual level of infeasibility or their level of soft constraint violations. The **objective** is to minimize the number of soft constraints violations in a *feasible* timetable. Soft constraint violations are evaluated in the following way:

- Count the number of occurrences of a student having just one class on a day (e.g. count 2 if a student has two days with only one class).
- Count the number of occurrences of a student having more than two classes consecutively (3 consecutively scores 1, 4 consecutively scores 2, 5 consecutively scores 3, etc.). Classes at the end of the day followed by classes at the beginning of the next day do not count as consecutive.
- Count the number of occurrences of a student having a class in the last timeslot of the day.

Twenty different sets of problem instances were provided for the competition. They are an extended version of the instances proposed by Socha et al. (2002) and both are constructed by a generator written by Ben Paechter. The instances have varying difficulty, but it is possible to find a feasible solution for all of them within the given computer time. All the instances have at least one perfect solution, that is a solution with no constraint violations, hard or soft, but it is unlikely to be found in the given computer time. Table 1 on the next page shows the data of all twenty instances.

The algorithms submitted should run on a single processor machine. Participants have to **benchmark** their machine with a program provided on the website. This program will indicate how much time participants can run their algorithm on their machines. The same version (and fixed parameters) of the algorithm should be used for all instances. “



Instance identifier	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
No. of events	400	400	400	400	350	350	350	400	440	400	400	400	400	350	350	440	350	400	400	350
No. of students	200	200	200	300	300	300	350	250	220	200	220	200	250	350	300	220	300	200	300	300
No. of rooms	10	10	10	10	10	10	10	10	11	10	10	10	10	10	10	11	10	10	10	10
Rooms/event	1.96	1.92	3.42	2.45	1.78	3.59	2.87	2.93	2.58	3.49	2.06	1.96	2.43	3.08	2.19	3.17	1.11	1.75	3.94	3.43
Events/student	17.75	17.23	17.70	17.43	17.78	17.77	17.48	17.58	17.36	17.78	17.41	17.57	17.69	17.42	17.58	17.75	17.67	17.56	17.71	17.49
Students/event	8.88	8.62	8.85	13.07	15.24	15.23	17.48	10.99	8.68	8.89	9.58	8.79	11.05	17.42	15.07	8.88	15.15	8.78	13.28	14.99

Table 1: Twenty Datasets of ITC 2003 (Chiardini Et Al., 2006)

5.2.2 WINNING ENTRY

The winning paper was submitted by Philipp Kostuch of Oxford University, Department of Statistics. The algorithm uses a three-phase approach. First an initial feasible solution is constructed while trying to put the least possible events in the end-of-day timeslots. Next, the sequence of the formed time-slots is changed in order to reduce the penalty score arising from the first two soft constraints, using Simulated Annealing. Finally pairs of events in different timeslots are exchanged (if feasibility is preserved) in order to further reduce the objective function, again using Simulated Annealing.

5.3 2007 COMPETITION[1]

In 2007 the second international timetabling competition was held. It built on the success of the first competition, but more depth and complexity was introduced in order to move further into real-world situations. The competition was composed of three tracks. Although there is much overlap, these tracks represent distinct problems within the area of educational timetabling both from a research and practical perspective. There were two tracks on course timetabling, curriculum-based and post

[1] All information can be found on: http://www.cs.qub.ac.uk/itc2007

enrolment-based, and one on examination timetabling. To recall the difference between these problems, see section 3.2, p. 8

This time a prize of £500 and a ticket to the 2008 PATAT Conference was awarded.

5.3.1 THE MODEL

I will discuss the post enrolment-based course timetabling track, as this is an extension of the model used in the 2003 competition. The problem consists of the following: a set of events that are to be scheduled into 45 timeslots (5 days of 9 hours each); a set of rooms in which events take place; a set of students who attend the events; and a set of features satisfied by rooms and required by events. Each student attends a number of events and each room has a size. This is exactly the same as in the 2003 competition described in section 5.2.1, p. 16 . In addition to this, some events can only be assigned to certain timeslots, and some events will be required to occur before other events in the timetable. So a feasible timetable is one where events have been assigned a timeslot and a room so that the following **hard constraints** are satisfied:

- no student attends more than one event at the same time;
- the room is big enough for all the attending students and satisfies all the features required by the event;
- only one event is put into each room in any timeslot;
- events are only assigned to timeslots that are pre-defined as available for those events;
- where specified, events are scheduled to occur in the correct order of the week.

Fourteen sets of problem instances are provided. The problem instances are set in such a way that it might not always be possible to schedule all of the events into the timetable in the given time without breaking some of the hard constraints. It will therefore be necessary for participants to not place some events in the timetable (or remove them later) in order to ensure that no hard constraints are being violated. These events will then be considered unplaced. This results in a **different evaluation** of the submitted solutions. First, the hard constraints are considered. If any of these are being violated then the solution will be disqualified. However, participants are allowed to leave certain events unplaced. If there are events that are not assigned to the timetable, the *distance to feasibility* is calculated. It is the total number of students that are required to attend each of the unplaced events. The **soft constraints** and the penalties for the objective function value for breaking the soft constraints are exactly the same as in the 2003 model.

A timetable's quality is now reflected by two values: the distance to feasibility, and the number of soft constraint violations. In order to compare two solutions, the following procedure is used: "First, we will look at the solution's Distance to Feasibility. The solution with the lowest value for this will be the winner. If the two solutions are tied, we will then look at the number of soft constraint violations. The winner will be the solution that has the lowest value here. "

5.3.2 WINNING ENTRY

The winning paper was submitted by Hadrien Cambazard, Emmanuel Hebrard, Barry O'Sullivan and Alexandre Papadopoulos of the Cork Constraint Computation Centre. The approach was a local search algorithm that was hybridized with a Constraint Programming approach. The paper with description of this algorithm can be found in the references.

6. HEURISTICS AND METAHEURISTICS IN UCT

For about 50 years there has been research in finding methods to construct timetables, and for the last 15 years-or-so there has been an increased interest in this field of research (MirHassani & Habibi, 2011) and especially in applying metaheuristics to it (Lewis, 2008). A wide variety of approaches can be found in the literature and has been tested on real data sets. These approaches can be roughly divided into four categories (Burke & Petrovic, 2002), (1) sequential methods, (2) cluster methods, (3) constraint-based approaches, and (4) metaheuristics. The following paragraphs will give a short description of each, as well as references to papers where they have been applied. It has to be noted that of course these categories are not strict and methods and algorithms can fall in between two categories or can be of a hybrid form.

6.1 HEURISTICS

6.1.1 SEQUENTIAL METHODS

When a sequential method is used to complete a timetable events are first ordered based on some sequencing strategy and then scheduled into the timetable in that order, in such a way that no events are in conflict with each other. The logical idea here is that events that are most difficult to schedule will be considered first. Some well-known sequencing strategies are Largest Degree First, Largest Weighted Degree First, Largest Coloured Degree First and Least Saturation First. A survey of these sequencing strategies can be found in Carter (1986) or Burke and Petrovic (2002). Application of these strategies was popular in the 1970's and 80's. Nowadays they can still be found in many papers, where they are often used to construct initial solutions to be used in metaheuristics. (Obit & Landa-Silva, 2011; Abdullah et al., 2010; Kostuch, 2005).

One widely-used and well-known heuristic based on the sequential method, is the graph-colouring problem. Timetabling problems are represented as graphs where events are shown as vertices, while conflicts between the events are represented by edges (de Werra, 1985). For example, if a student has to attend two events there will be an edge between the vertices which represents this conflict. In this way the construction of a conflict-free timetable can be modelled as a graph colouring problem. Each time period in the timetable corresponds to a colour in the graph colouring problem and the vertices of a graph are coloured in such a way so that no two vertices that are connected by an edge are coloured by the same colour. A variety of graph colouring heuristics for constructing conflict-free timetables can be found in Brelaz (1979). Although graph-colouring methods have been very useful, they are, as a stand-alone method, absolutely not powerful enough to cope with the complexity of today's timetabling problems. Combined with other heuristics however they can be very valuable, as is proven to us by Kostuch, the winner of the International Timetabling Competition of 2003 (see supra p. 18). In his winning algorithm he used a sequential colouring algorithm to construct an initial timetable. (Kostuch 2005)

6.1.2 CLUSTER METHODS

In cluster methods courses or events are subdivided into groups, 'clusters', in such a way that these groups satisfy the hard constraints. Next the groups or clusters are assigned to timeslots while trying to satisfy the soft constraints as much as possible. Different optimization techniques can be used to schedule the groups of events into timeslots, an example of this can be found in Balakrishnan et al., 1992. The main weakness of cluster methods is that the clusters of events are formed at the start of the algorithm and remain the same throughout the execution. This inflexibility may well lead to a poor quality timetable. (Burke & Petrovic, 2002).

The performance of these methods is again very poor compared to today's state-of-the-art solutions. However, clustering can still prove to be very useful when it is applied within a metaheuristic or another solution procedure. In this case the clustering will be done with flexibility and allows the researcher to analyze relationships between different groups of events and use them smartly.

6.1.3 CONSTRAINT-BASED APPROACHES

In a constraint-based approach a timetabling problem is modeled as a Constraint Satisfaction Problem (CSP). A CSP consists of a set of variables (events or courses) to which values (rooms, timeslots, teachers) have to be assigned while satisfying a number of constraints and minimizing an objective function. Many combinatorial optimization problems, such as the timetabling problem can be formulated as a CSP. (Brailsford, Potts, Smith, 1999).

Usually a number of rules is defined for assigning resources to events. When no rule is applicable to the current partial solution a backtracking method is applied until a solution is found that satisfies all constraints. With backtracking one or more events are removed from the partial solution so that the heuristic can continue. Several backtracking strategies exist and they can be used in combination with other heuristics. An example of backtracking can be found in Burke, Newall and Weare (1998).

In the International Timetabling Competition of 2007 both the winner and runner-up used a CSP formulation and solver as part of their hybrid algorithm. (Cambazard et al., 2007; Atsuta et al., 2007) This shows that constraint-based approaches can be very powerful.

6.2 METAHEURISTICS

The three approaches described above are all heuristic methods. “Although these heuristics show great efficiency in constructing a timetabling solution quickly, the quality of the solution is often inferior to that produced by metaheuristic or hybrid metaheuristic methods.” As stated before, “nowadays these heuristics are normally used in the construction of initial solution(s) for metaheuristic methods.” (Al-Betar & Khader, 2010, p. 4). While a heuristic method tries to find a solution based on a systematic, logical, problem-specific approach, a metaheuristic goes beyond this. The Metaheuristics Network, a European research project that was run between 2000 and 2004 (see supra, p. 16) defines metaheuristics as follows: “A metaheuristic is a set of concepts that can be used to define heuristic methods that can be applied to a wide set of different problems. In other words, a metaheuristic can be seen as a general algorithmic framework which can be applied to different optimization problems with relatively few modifications to make them adapted to a specific problem. ”Given these characteristics, and given the fact that timetabling problems can vary significantly depending on their size, their constraints, the preferences of their institutions, … it seems that metaheuristics are quite suitable in this problem domain (Lewis, 2008). It is generally agreed upon that “the emergence of metaheuristics for solving difficult timetabling problems has been one of the most notable accomplishments of the last two decades or even earlier” (Al-Betar & Khader, 2010, p. 4).

On their website the Metaheuristics Network states that there are five main metaheuristic paradigms, namely (1) Evolutionary Algorithms (EA), (2) Ant-Colony Optimization, (3) Tabu search (TS), (4) Simulated Annealing (SA), and (5) (Iterated) Local Search (ILS). Of course all five of these, and other variants, have been numerously applied to the timetabling problem.

Different ways exist to classify metaheuristics: nature-inspired vs. non-nature inspired, dynamic vs. static objective function, one vs. various neighborhood structures, memory usage vs. memore-less methods, … But the most commonly way to classify metaheuristics is whether they are population-based or local-search based (Blum & Roli, 2003).

Local search-based methods consider one solution at a time. The search-space around this solution is explored iteratively, through the investigation of neighborhoods, and the solution is changed whenever an improvement is found. The main strength of these methods is their ability of fine-tuning the solution to an optimum fast and more structurally than population-based methods, the main disadvantage is that they have a tendency to get stuck in a local optimum. This is mainly due to the focus on exploitation rather than exploration, or in other words intensification rather than diversification, which means that they move in one direction (i.e. towards the local optimum) without performing a wider scan of the entire search space. Most local-search methods however try to avoid getting stuck in local optima by using some kind of smart technique, such as accepting worse solutions (SA, hill-climbing), keeping a list of prohibited moves (TS), … Although this improves the performance it's no guarantee for finding the optimal solution. Applications of local-search based methods can be found in; Socha et al. (2002), this paper tackles a problem with small, large and medium instances that has also been used in many papers as a benchmark dataset, with an *Iterated Local Search* as part of a hybrid algorithm; Kostuch (2005) applies *Simulated Annealing* in a very succesful way in the 2003 International Timetabling Competition; Abdullah et al. (2005) apply a *Very Large Neighborhood Search* to the problem, and they conclude that their approach is most suitable for smaller problems (i.e. the small and medium instances of Socha et al., 2002). A *Tabu Search* approach can be found in Burke et al., (2004) or Di Gaspero and Schaerf (2001).

In 2002 Rossi-Doria et al. published a paper in which they ask an interesting question: "*Is there one kind of metaheuristic algorithm that performs significantly better than others?*" The main goal of the paper was to attempt an unbiased comparison of the performance of straightforward implementations of five different metaheuristics. The authors conclude that Tabu Search and Iterated Local Search show better results with respect to finding a feasible timetable, but when a feasible solution is found, Simulated Annealing performed better in minimizing soft constraint violations. Except for ILS, TS and SA, also Evolutionary Algorithm and Ant-Colony Optimization were part of the comparison. Their overall conclusion was that there is no certain metaheuristic that always outperforms the others. As UCTP's can be very different according to their size and extent and tightness of constraints, each solution approach, even with metaheuristics, should be at least partially adjusted to the problem at hand.

One more local-search based method I would like to highlight is the relatively new Great Deluge Algorithm (GDA). It was first proposed by Dueck (1993), and the underlying logic is very similar to that of SA, but according to Dueck it often outperforms it. Applications of the GDA can be found in Landa-Silva and Obit (2008) or McMullan et al. (2007)

Population-based methods consider many solutions at a time. During the execution of the algorithm, existing solutions are recombined to obtain new ones. Unfortunately, the solutions obtained with population-based methods are often of a poorer quality than those of local search-based methods as they are worse at finding the exact optimal solution in the search space region to which the algorithm converges (Fesanghary et al. 2008). The reason for this ‘weakness’ is that population-based methods focus more on exploration or diversification rather than exploitation or intensification; they explore the entire search space for solutions without searching for possible local improvements of obtained solutions. Another drawback is that they often require more time compared to local-search based methods. (Chiarandini et al. 2006*).* Applications of population-based methods can be found in; Erben and Keppler (1996), this paper describes a purely Genetic Algorithm (GA) with a mutation and crossover operator for a heavily constrained UCTP. Lewis and Paechter (2004) implement and analyze the performance of four different crossover operators. They conclude that the crossovers are not state-of-the-art and that the results could be significantly improved by implementing local searches and/or smart mutations. Socha et al. (2002) developed a Min-Max Ant system, a modified Ant Colony Optimization algorithm for the UCTP. Malim et al. (2006) apply three different Artificial Immune System which show good results for relatively small problem instances.

6.3 HYBRID ALGORITHMS

In the light of the above, namely the different advantages and drawbacks of local-search versus population-based methods, it seems reasonable to develop algorithms that use a combination of these techniques through which the advantages of both can be fully exploited. In a paper of 2003 Blum and Roli explain this as follows: “In summary, population-based methods are better in identifying promising areas in the search space, whereas trajectory methods are better in exploring promising areas in the search space. Thus, metaheuristic hybrids that in some way manage to combine the advantage of population-based methods with the strength of trajectory methods are often very successful”. This is what, in the past decade-or-so many researchers have been doing, with very promising results. Nowadays almost every solution approach developed is hybrid in at least some way, and when ‘pure’ metaheuristics are studied for a certain problem, it is usually with the goal to optimize them for later use in hybrid methods. The specific combination of local-search and population-based methods is also referred to as Memetic Algorithms. The combination or hybridization of different methods gives way to many research directions, which are being explored by practitioners around the world. Applications of hybrid techniques can be found in: Abdullah et al. (2010, 2007), Yang and Naseem Jat (2011), Chiarandini (2006), Fesanghary (2008), Landa-Silva and Obit (2011) and Blum (2011).

As a final paragraph of this overview of methods used for the UCTP I would like to mention the classifications of algorithms proposed by Lewis (2008). After a survey of the literature Lewis states that most metaheuristic algorithms for timetabling fall into one of the three following categories:

- **One-stage optimization algorithms:** a satisfaction of both hard and soft constraints is attempted simultaneously.
- **Two-stage optimization algorithms:** a satisfaction of soft constraints is attempted only once a feasible timetable has been found.
- **Algorithms that allow relaxations:** violations of hard constraints are disallowed from the outset by relaxing some other feature of the problem, and attempts are then made to try to satisfy the soft constraints, whilst also giving consideration to the task of eliminating these relaxations.

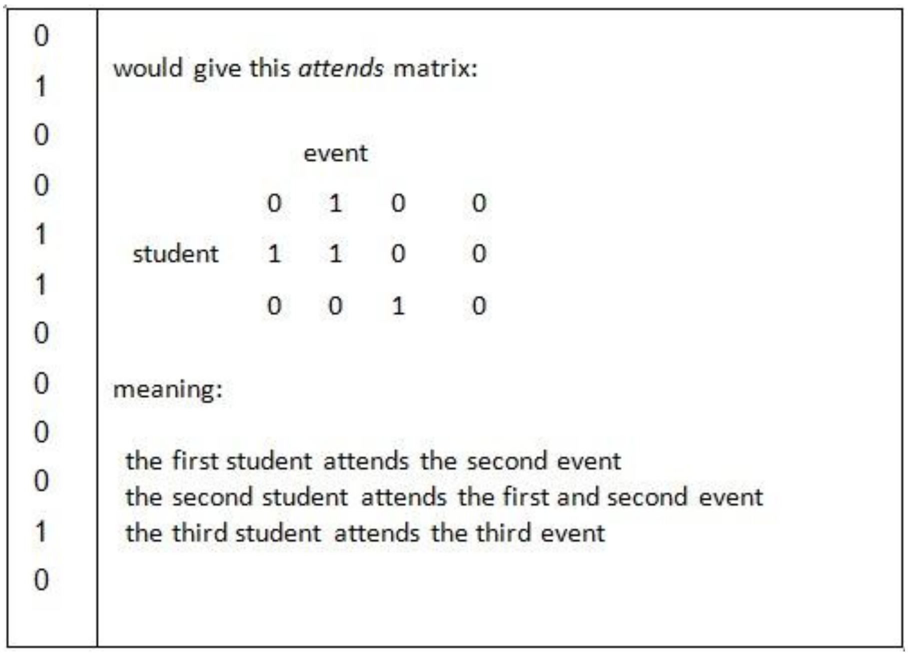
In the paper of Rossi-Doria et al. (2002) where a comparative study of the five basic metaheuristics is done, the authors suggest, for future work to experiment with methods that split the search into two phases. In the first phase feasibility is sought with appropriate heuristics, while in the second phase soft constraint violations can be minimized while containing feasibility. So this paper, which was a result of the cooperation of twelve experienced and eminent researchers, suggests that **two-stage optimization algorithms** give way to promising results.

7. THE ALGORITHM

7.1 VARIABLE REPRESENTATION AND DATA PREPROCESSING

Before starting to write the program code, it is essential to choose a good representation of the variables used. The algorithm should run within a given time limit, so efficient data structures and variable representation are very important. First we take a look at the input format of the data as given on the competition's website:

First line:
Number of events, number of rooms, number of features, number of students.
One line for each room:
Room size.
One line for each student/event:
A zero or one. Zero means that the student does not attend the event, one means that he does attend the event. In the order of these the event changes more quickly. For example, if there were 3 students and 4 events then the following:



```
0
1
0
0
1
1
0
0
0
0
1
0
```

would give this *attends* matrix:

$$\begin{array}{ccccc} & \multicolumn{4}{c}{\text{event}} \\ & 0 & 1 & 0 & 0 \\ \text{student} & 1 & 1 & 0 & 0 \\ & 0 & 0 & 1 & 0 \end{array}$$

meaning:

the first student attends the second event
the second student attends the first and second event
the third student attends the third event

Figure 1: Data Input Format ITC 2003 (www.idsia.ch/Files)

One line for each room/feature:
In the same format as the student/event matrix.
One line for each event/feature:
In the same format as the student/event matrix.

Based on this format I created **five initial variables**. Two arrays, one to save the total number of the events, rooms, features and students, and one to save the size of the different rooms; and three matrices, one student-event matrix, one room-feature matrix, and one event-feature matrix. Because the program will be run on different instances with different sizes the matrices and the room size array are created dynamically, based on the sizes given in the first array.

The information contained within these matrices can be processed into different matrices which contain the same information in a more compact, easy-to-use way. To do this we take a look at the problem's constraints. HC1 says that no student can attend more than one event at the same time. This means that two or more events that are taken by the same student cannot be scheduled in the same timeslot. If we analyze the information given in the student-event matrix considering this hard constraint, we can create an **event-conflict matrix**. This matrix of dimension events x events indicates directly which events cannot be scheduled at the same time.

Next we look at HC2 which says that every event should be scheduled in a suitable room, meaning it is big enough and has all required features available. For this constraint we can aggregate the information given in the room size array, room-feature matrix, and event-feature matrix into an **event-room matrix**, which directly indicates the suitable rooms per event. With this data preprocessing the information of the instance is represented in these two matrices.

Before we start solving the problem, we can implement another data manipulation that can speed up the algorithm. Given the event-room matrix we can check if there are events that can be held in only one specific room. If there are such events, and if there are multiple events which have the same room as their only option, we can use this information smartly. That is, events that have the same room as their only option cannot be scheduled in the same timeslot, as this would give either a room suitability conflict (HC2) or a room which is overbooked (HC3). Therefor we can update the event-conflict matrix with this information (Kostuch, 2003).

The *representation of the roster* itself is a **chromosome representation** in the form of a two dimensional matrix (rooms x timeslots) which has the value of the event scheduled in that room and that timeslot, and a value of minus one if no event is scheduled. To speed up the algorithm and to ensure flexibility when implementing different heuristics I also keep an **event ID structure** for every event, which contains the day, hour and room in which that event is scheduled This enables the algorithm to quickly find the location of an event in the roster. It is in fact another form of chromosome representation. Additionally I use a **student-chromosome** of dimension students x timeslot, which has the value of the event that a particular student has in that particular timeslot. These last two matrices are kept to enable cheap evaluation and better constructive heuristics.

7.2 FIRST PHASE: FINDING FEASIBILITY

As is proposed by Rossi-Doria et al. (2002), and as is done in the majority of recent papers on UCT that use metaheuristics, my approach is a two-stage optimization algorithm. In this section I will describe the first phase: finding a feasible roster. This first phase will be called the **Initialization Heuristic (IH)** and will consist of a Constructive Heuristic (CH) and if needed a Local Search (LS). I created three different IH's which I will describe hereafter.

I will test these heuristics on instance one and instance four of the competition. If we look at the results of Kostuch, the winner of ITC 2003, in figure 2 we can see that instance one has a medium difficulty and instance four has a high difficulty. I will not use instance five, the most difficult one to test the IH's because, if we look at table 1 on p. 18 we see that instance five has fifty events less compared to instance four. This implies that finding feasibility for instance five is less difficult. From now on I will refer to instance one as the 'medium instance' and to instance four as the 'hard instance'. In section 7.2.4. I will compare the performance of the IH's in terms of speed and diversity and choose one of them to use as IH for the second phase of my algorithm.

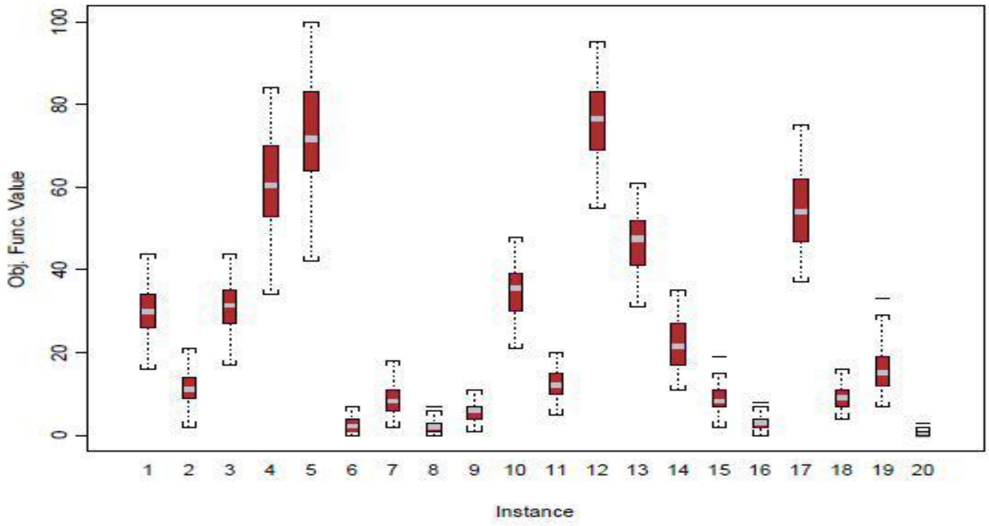
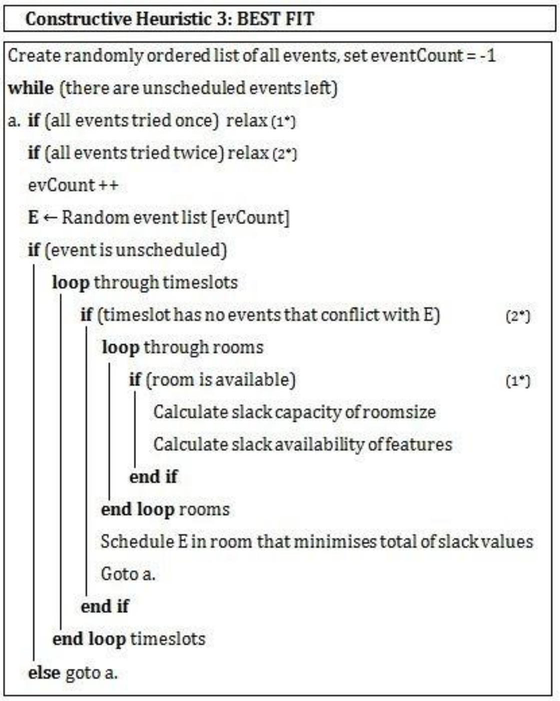


Figure 2: Results ITC 2003 Kostuch (Kostuch, 2005)

7.2.1 IH 1: BEST FIT HEURISTIC AND VARIABLE NEIGHBORHOOD DESCENT

The constructive heuristic of IH 1 is a **best fit heuristic**. More precisely the CH selects events at random and then loops through the timetable, until all events are selected once. Whenever a feasible timeslot for that event is encountered (i.e. a timeslot where no events that conflict with the selected event are scheduled), the CH selects the best, still available room for that event in that timeslot and schedules it. 'Best room' means the room with the least slack capacity and the least slack availability of features. In this loop the CH considers all three Hard Constraints . Next, the same loop is executed but HC 3, room availability, is relaxed. If after this loop there are still events unscheduled, HC 1, conflicting events, is relaxed. If after this loop there still remain events unscheduled, also HC 2, room suitability, is relaxed and all remaining events are scheduled. The pseudo-code can be found in figure 3.



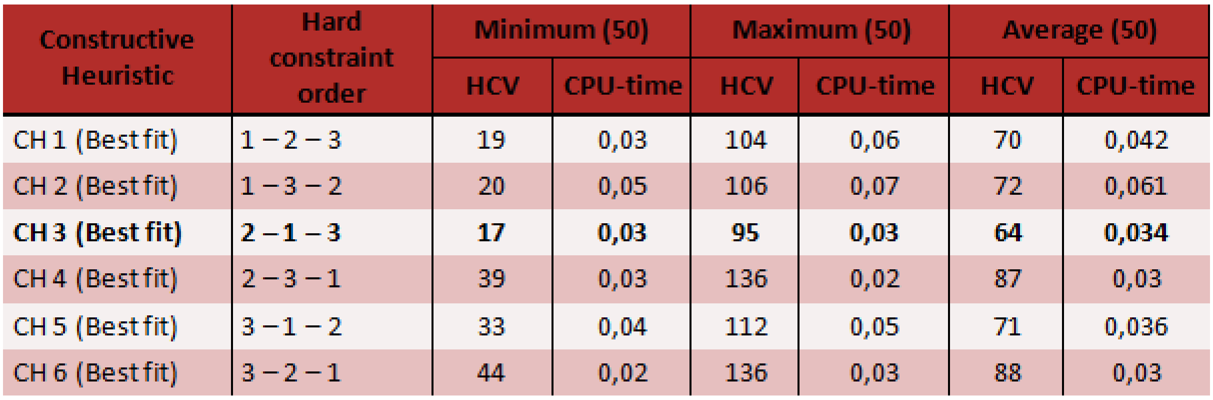
```
Constructive Heuristic 3: BEST FIT

Create randomly ordered list of all events, set eventCount = -1
while (there are unscheduled events left)
a. if (all events tried once) relax (1*)
   if (all events tried twice) relax (2*)
   evCount ++
   E ← Random event list [evCount]
   if (event is unscheduled)
      loop through timeslots
         if (timeslot has no events that conflict with E)          (2*)
            loop through rooms
               if (room is available)                              (1*)
                  Calculate slack capacity of roomsize
                  Calculate slack availability of features
               end if
            end loop rooms
            Schedule E in room that minimises total of slack values
            Goto a.
         end if
      end loop timeslots
   else goto a.
```

Figure 3: Pseudo-Code Constructive Heuristic 3: Best Fit

The order of relaxation of HC's is based on preliminary tests, from which the results can be found in Table 2 for the medium instance, and in Table 3 for the hard instance. Out of fifty runs, the minimum, maximum and average of Hard Constraint Violations (HCV's) is given, together with the CPU-time used for that specific result. Hard constraint order 1 – 2 – 3 means that HC 3 is relaxed first, then HC 2, and finally HC 1.

Constructive Heuristic	Hard constraint order	Minimum (50)		Maximum (50)		Average (50)	
		HCV	CPU-time	HCV	CPU-time	HCV	CPU-time
CH 1 (Best fit)	**1 – 2 – 3**	**1**	**0,17**	**20**	**0,17**	**6**	**0,16**
CH 2 (Best fit)	1 – 3 – 2	0	0,14	19	0,22	8	0,18
CH 3 (Best fit)	2 – 1 – 3	1	0,12	21	0,14	7	0,13
CH 4 (Best fit)	2 – 3 – 1	4	0,25	42	0,12	21	0,13
CH 5 (Best fit)	3 – 1 – 2	2	0,14	21	0,14	9	0,14
CH 6 (Best fit)	3 – 2 – 1	2	0,12	53	0,12	25	0,12

Table 2: Hard Constraint Violations Constructive Heuristics Best Fit – Instance 1



Constructive Heuristic	Hard constraint order	Minimum (50)		Maximum (50)		Average (50)	
		HCV	CPU-time	HCV	CPU-time	HCV	CPU-time
CH 1 (Best fit)	1 – 2 – 3	19	0,03	104	0,06	70	0,042
CH 2 (Best fit)	1 – 3 – 2	20	0,05	106	0,07	72	0,061
CH 3 (Best fit)	**2 – 1 – 3**	**17**	**0,03**	**95**	**0,03**	**64**	**0,034**
CH 4 (Best fit)	2 – 3 – 1	39	0,03	136	0,02	87	0,03
CH 5 (Best fit)	3 – 1 – 2	33	0,04	112	0,05	71	0,036
CH 6 (Best fit)	3 – 2 – 1	44	0,02	136	0,03	88	0,03

Table 3: Hard Constraint Violations Constructive Heuristics Best Fit – Instance 4

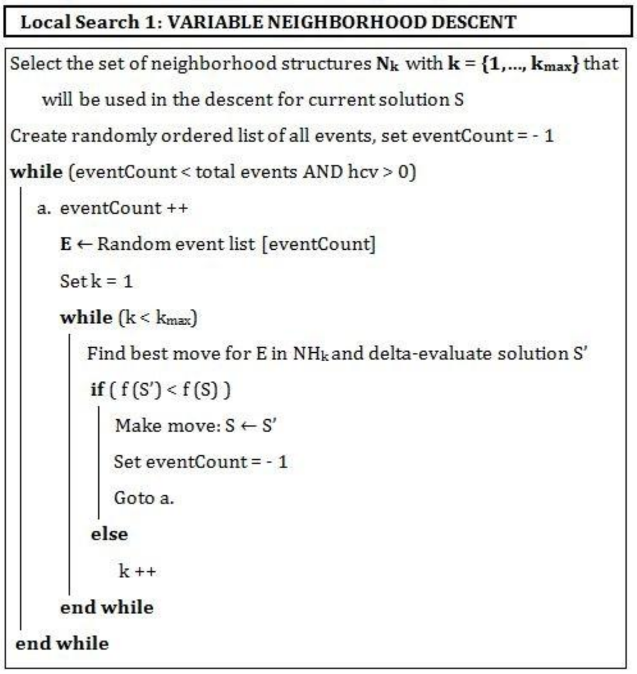
When HC 1 is relaxed first, the results are poorest. This makes sense once we analyze the hard constraints. When two 'conflicting events' are scheduled at the same moment, and thus violating HC1, the penalty arising from this is multiplied by the number of students taking both courses. Whereas allocations that violate HC 2 (an event scheduled in an unsuited room) or HC 3 (an event scheduled in an occupied room), the penalty for this is just one per violation, disregarding the amount of students affected by it. The effect of which constraint is relaxed second is not so significant. This can be understood by the fact that there are very few unscheduled events left, usually between zero and five, after the heuristics executes the first two loops through all events (where the first loop takes all HC's into account, and the second loop drops one HC).

For the first initialization heuristic I decided to select CH 3 as constructive heuristic. Out of fifty runs, the CH gives an average of seven HCV's for the medium instance and an average of 64 HCV's for the hard instance. Remarkable in the results for the medium instance is that CH 2 constructs a feasible timetable at once. CH 1, 2, 3, and 5 tend to do this from time to time. The CPU-times do not vary significantly.

So an initial solution is created, and the LS can be applied to reach feasibility. This LS is a **Variable Neighborhood Descent (VND)**, as proposed by Hansen (1997), and is based on three facts:

- "A local minimum w.r.t. one neighborhood structure is not necessary so with another;
- A global minimum is a local minimum w.r.t. all possible neighborhoods;
- For many problems local minima w.r.t. one or several neighborhoods are relatively close to each other." (Hansen, 1997, p2)

These three facts can be used in a deterministic way to find feasibility. This is exactly what VND does. During the search it scans different neighborhoods and selects the best move per neighborhood. If that move reduces the HCV's it accepts the moves and the search continues with the newly accepted solution. The pseudo-code of my VND can be found in figure 4.



```
Local Search 1: VARIABLE NEIGHBORHOOD DESCENT

Select the set of neighborhood structures Nk with k = {1,..., kmax} that
    will be used in the descent for current solution S
Create randomly ordered list of all events, set eventCount = - 1
while (eventCount < total events AND hcv > 0)
    a. eventCount ++
       E ← Random event list [eventCount]
       Set k = 1
       while (k < kmax)
           Find best move for E in NHk and delta-evaluate solution S'
           if ( f (S') < f (S) )
               Make move: S ← S'
               Set eventCount = - 1
               Goto a.
           else
               k ++
       end while
end while
```

Figure 4: Pseudo-Code Local Search 1: Variable Neighborhood Descent

Hansen suggests that the optimal number of neighborhoods used is often two. The neighborhoods I used are:

- **N_1** : Select one event that causes a hard constraint violation at random and move it to a feasible timeslot and room.
- **N_2** : Select one event that causes a hard constraint violation at random and swap it with another event.

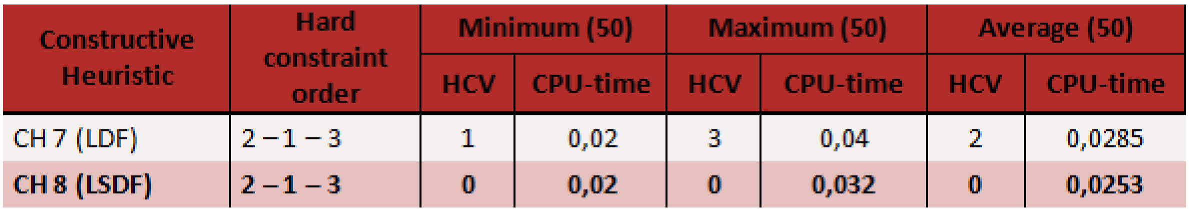
Separately these neighborhoods do not give satisfying results. This can be well understood by the fact that one neighborhood, without the other, doesn't have the opportunity to try out the entire search space. If N_2 would be applied without N_1 the timeslots and rooms that have no event allocated to them, would always stay empty. Obviously this would severely limit the strength of the local search. On the other hand, if N_1 would be applied without N_2, events could only be moved to empty timeslots. In theory this neighborhood has the possibility to do the same as N_2, namely swapping two events by permuting them through three locations, from which one is empty. Nevertheless, it's not hard to understand that when used complementary these neighborhoods perform best.

When I use the two **neighborhoods N$_1$** and **N$_2$** in a VND algorithm, it gives satisfying results for the medium instance: the VND is able to find feasible rosters. To speed up the search evaluation of possible moves is done with delta-evaluation. So instead of recalculating the fitness of the complete roster, only the effect on the fitness of the move under consideration is calculated. Now and then the search gets stuck in a local optimum with one or two HCV's. If this is the case I discard the solution and restart the IH. For the hard instance however, the LS doesn't find feasible rosters. This means that this IH will not be applicable to all instances.

7.2.2 IH 2: SEQUENTIAL HEURISTIC AND VND

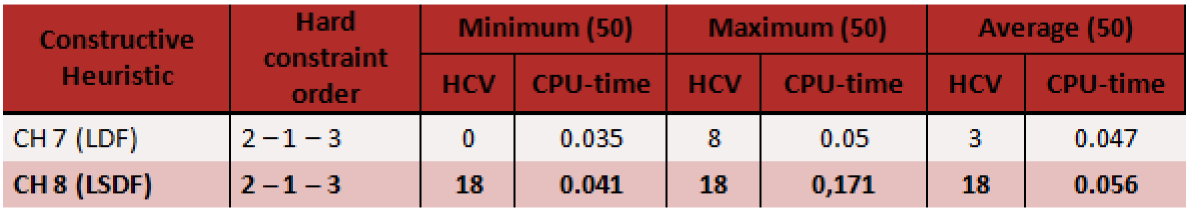
The constructive heuristic of IH 2 uses a **sequencing strategy** to schedule events in the timetable. The sequencing strategy estimates how difficult it will be to schedule each event, and then puts the events in the order of decreasing difficulty. I created two sequencing heuristics. The first is called **Largest Degree First** (LDF). Per event the total number of conflicting events (events it cannot be scheduled in the same timeslot with) is calculated. The events with the greatest number of conflicts are scheduled first, ties are broken randomly. The second strategy, **Least Saturation Degree First** (LSDF), considers the rooms. The events with the least possibilities of rooms to be scheduled in are selected first. In this case Largest Degree is used to break ties.

When the events are ordered in the right sequence, the heuristic continues in the same way as the CH of IH 1. The pseudo-code is the same as in figure 4, except the first line would be 'order events according to sequencing strategy'. Another small difference is that this time the heuristics runs through the timeslots in a random order. This is done to increase randomness for when the heuristic would be used to fill a population that needs diverse members. Table 4 and 5 show the results of fifty runs for both CH's, on both instances.



Constructive Heuristic	Hard constraint order	Minimum (50)		Maximum (50)		Average (50)	
		HCV	CPU-time	HCV	CPU-time	HCV	CPU-time
CH 7 (LDF)	2 – 1 – 3	1	0,02	3	0,04	2	0,0285
CH 8 (LSDF)	**2 – 1 – 3**	**0**	**0,02**	**0**	**0,032**	**0**	**0,0253**

Table 4: Hard Constraint Violations Sequential Constructive Heuristics – Instance 1



Constructive Heuristic	Hard constraint order	Minimum (50)		Maximum (50)		Average (50)	
		HCV	CPU-time	HCV	CPU-time	HCV	CPU-time
CH 7 (LDF)	2 – 1 – 3	0	0.035	8	0.05	3	0.047
CH 8 (LSDF)	**2 – 1 – 3**	**18**	**0.041**	**18**	**0,171**	**18**	**0.056**

Table 5: Hard Constraint Violations Sequential Constructive Heuristics – Instance 4

We see that for the medium instance, CH 8 generates feasible timetables every time. CH 7 also gives very good results with an average of two HCV's.

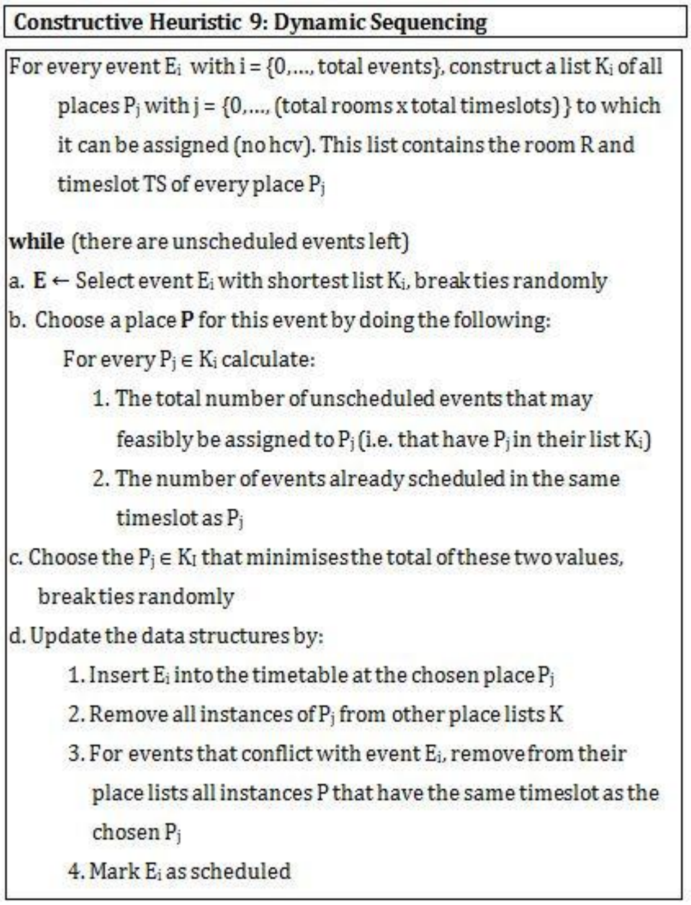
For the hard instance results are different. CH 7 gives comparable results as for the medium instance, but CH 8 always initializes timetables with eighteen HCV's. The rosters are however different, which can be concluded from their difference in soft constraint violations (SCV) or directly from calculating the diversity between the constructed rosters (see infra section 7.2.4). The reason that there are eighteen HCV's every time is that the same three events are always scheduled last, as is dictated by the sequencing strategy. And although the timetable is filled differently (because the order of timeslots is chosen randomly), these three last events always cause eighteen HCV's, from which fifteen are caused by students having two events at the same time, and three are caused by a room that has two events scheduled in it at the same time.

When these initial timetables are constructed, the same LS as for IH 1, namely VND, is applied to them. This gives us two new IH's: IH 2a consists of CH 7 followed by VND and IH 2b consists of CH 8 also followed by VND. Both of them can produce feasible rosters. Which one performs best will become clear in section 7.2.4.

7.2.3 IH 3: DYNAMIC SEQUENCING

The last initialization heuristic consist of only a constructive heuristic. This CH is again based on a sequential strategy. Compared to those described above, this strategy is slightly more complex, and it is dynamic throughout its execution. This means that whenever an event is scheduled, the sequencing order is recalculated. Another, slightly simpler example of a dynamic sequencing strategy is Largest Coloured Degree First, where events with the greatest number of conflicting events *that have already been scheduled* are scheduled first.

Our final CH was proposed by Arntzen and Løkketangen (2003), and also implemented by Lewis and Paechter (2004). It orders events based on the total amount of places (a place being the combination of a certain timeslot and room) it can possibly be scheduled in. Events with the least possibilities are scheduled first, ties are broken randomly. The heuristic can be seen as an extended version of the LSDF heuristic. The pseudo-code is shown in figure 5.



```
Constructive Heuristic 9: Dynamic Sequencing

For every event $E_i$ with i = {0,..., total events}, construct a list $K_i$ of all
    places $P_j$ with j = {0,..., (total rooms x total timeslots)} to which
    it can be assigned (no hcv). This list contains the room R and
    timeslot TS of every place $P_j$

while (there are unscheduled events left)
a. E ← Select event $E_i$ with shortest list $K_i$, break ties randomly
b. Choose a place P for this event by doing the following:
      For every $P_j \in K_i$ calculate:
         1. The total number of unscheduled events that may
            feasibly be assigned to $P_j$ (i.e. that have $P_j$ in their list $K_i$)
         2. The number of events already scheduled in the same
            timeslot as $P_j$
c. Choose the $P_j \in K_I$ that minimises the total of these two values,
   break ties randomly
d. Update the data structures by:
      1. Insert $E_i$ into the timetable at the chosen place $P_j$
      2. Remove all instances of $P_j$ from other place lists K
      3. For events that conflict with event $E_i$, remove from their
         place lists all instances P that have the same timeslot as the
         chosen $P_j$
      4. Mark $E_i$ as scheduled
```

Figure 5: Pseudo-Code Constructive Heuristic 9: Dynamic Sequencing

Table 6 and 7 show the results of fifty runs. For every instance, it immediately generates feasible timetables. Therefore no local search is needed, and this gives us the last initialization heuristic IH 3. Occasionally it happens that an event ends up with an empty place list, so it cannot be scheduled. If this is the case, I discard the solution and restart the IH. Remarkable is that this CH needs a lot more CPU-time to create a timetable. This can be understood by the fact that it works dynamically and thus needs a more time.

Constructive Heuristic	Hard constraint order	Minimum (50)		Maximum (50)		Average (50)	
		HCV	CPU-time	HCV	CPU-time	HCV	CPU-time
CH 9 (Dynamic)	/	0	1,67	0	1,81	0	1,74

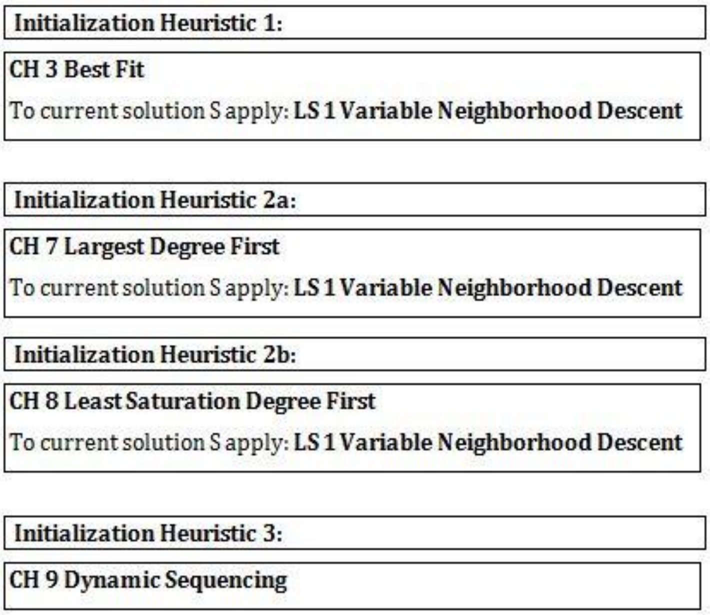
Table 6: Hard Constraint Violations Constructive Heuristic Dynamic Sequencing – Instance 1

Constructive Heuristic	Hard constraint order	Minimum (50)		Maximum (50)		Average (50)	
		HCV	CPU-time	HCV	CPU-time	HCV	CPU-time
CH 9 (Dynamic)	/	0	2,082	0	3,278	0	2,403

Table 7: Hard Constraint Violations Constructive Heuristic Dynamic Sequencing – Instance 4

7.2.4 COMPARISON OF IH'S

Before I compare the three IH's, I would like to emphasize the fact that each of them is able to produce feasible timetables (except IH 1 for the hard instances). If we reflect back to the problem at hand, this means that these are timetables that could be effectively used by a university. No student has more than one class at the same moment, no course has to take place in a room that is unsuited for it, and no room has two events scheduled at the same time. The only 'problems' that the timetable now causes is that sometimes students have more than two classes in a row, a class in the last hour of the day, or only one class in a whole day. On the competition's website the following can be read about the instances: "*The instances have varying difficulty, but you should expect to be able to find a feasible solution for all of them within the given computer time (but probably not with the first versions of your program, and perhaps not on every run).*" So, without exaggerating, I am pleased to have found several initialization heuristics that find feasible timetables for every instance. I will try to improve the quality of the roster during 'Phase 2: Optimization' (see infra, p. 38). Before moving on to phase two however, I will select one IH based on its performance in terms of speed and diversity when creating a population of feasible timetables. This because the second phase will consist of an evolutionary algorithm, and because the algorithm should run within a given time limit. Figure 6 gives an overview of the IH's.



Initialization Heuristic 1:

CH 3 Best Fit
To current solution S apply: **LS 1 Variable Neighborhood Descent**

Initialization Heuristic 2a:

CH 7 Largest Degree First
To current solution S apply: **LS 1 Variable Neighborhood Descent**

Initialization Heuristic 2b:

CH 8 Least Saturation Degree First
To current solution S apply: **LS 1 Variable Neighborhood Descent**

Initialization Heuristic 3:

CH 9 Dynamic Sequencing

Figure 6: Overview Initialization Heuristics

Table 8 and 9 show the results of the execution of the IH's on both instances. Out of ten runs the maximum, minimum and average 'population diversity' is given, together with the CPU-time used for that specific result, expressed in seconds. The diversity is calculated as the total number of *identical* allocation between two rosters. So actually it indicates the ‘non-diversity’. The population diversity is then calculated as the average of identical allocations between two rosters over the created population. So for example, in table 8, 13 is the average population diversity of the most diverse population out of ten populations created with IH 2b. The population size was set to twenty.

Initialization Heuristic	Minimum (10)		Maximum (10)		Average (10)	
	Population Diversity	CPU-time	Population Diversity	CPU-time	Population Diversity	CPU-time
IH 1	25	177,419	28	194,3	26	208,552
IH 2a	15	65,89	17	87,099	16	80,962
IH 2b	**13**	**6,474**	**16**	**6,802**	**14**	**6,765**
IH 3	25	35,49	27	44,171	26	42,325

Table 8: Performance of Initialization Heuristics for Creating Population – Instance 1

Initialization Heuristic	Minimum (10)		Maximum (10)		Average (10)	
	Population Diversity	CPU-time	Population Diversity	CPU-time	Population Diversity	CPU-time
IH 1	/	/	/	/	/	/
IH 2a	**17**	**29,266**	**19**	**39,546**	**18**	**45,317**
IH 2b	14	160,216	20	179,26	17	167,36
IH 3	31	64,826	34	68,384	32	71,873

Table 9: Performance of Initialization Heuristics for Creating Population – Instance 4

For the medium instance, IH 2b outperforms the others, in terms of diversity as well as speed. Speed is important because the faster phase one is executed, the more time can be allocated to phase two: optimization. For the hard instance IH 2a performs best. The rules of the ITC however, state that the complete algorithm should be exactly the same for all instances, therefore I will use IH3 as initialization heuristic for phase one. It’s performance in terms of speed comes second for both instances, and the diversity in the population is definitely at an acceptable level. Table 10 shows the results, in terms of SCV’s and cpu-time of a single execution of IH 3 on every instance of the problem. A feasible timetable was found every time. With these results we can now confidently move on to phase two.

Instance	1	2	3	4	5	6	7	8	9	10
SCV	885	919	844	1176	1326	1285	1562	1061	1006	892
CPU-time	1,836	1,914	3,572	2,344	1,112	2,902	2,101	3,116	2,916	3,782
Instance	11	12	13	14	15	16	17	18	19	20
SCV	961	943	1137	1486	1408	967	1384	893	1362	1314
CPU-time	2,07	1,614	2,282	1,98	1,594	4,842	0,55	1,743	4,344	3,462

Table 10: Initialization Heuristic 3 Tested on all Competition Instances

7.3 SECOND PHASE: OPTIMIZATION

As discussed in section 6 there are numerous methods to approach the timetabling problem. The best results are currently obtained by hybrid algorithms, and thus my attempt to tackle the ITC 2003 problem instances will also be of a hybrid form. I will describe the methods that I tested and/or used in the following sections. Test results to obtain the ideal composition of my algorithm , outcomes of parameter fine-tuning, and other experimental results will be given in section 8: Test Design and Experimental Results. The following sections are a pure theoretical description of the components of the algorithm.

7.3.1 HYBRID EVOLUTIONARY ALGORITHM

A schematic overview of the complete algorithm are given in figure 7. As discussed before an initial population is generated in phase one. Phase two begins by selecting one solution from the population with a selection operator. Next a mutation operator and the Non-Linear Great Deluge Algorithm (NLGDA) are applied to the solution. If the newly obtained timetable is better than the worst timetable in the population it replaces it. The algorithm continues like this until the maximum cpu-time is reached and then the best solution from the population is selected as the final result.

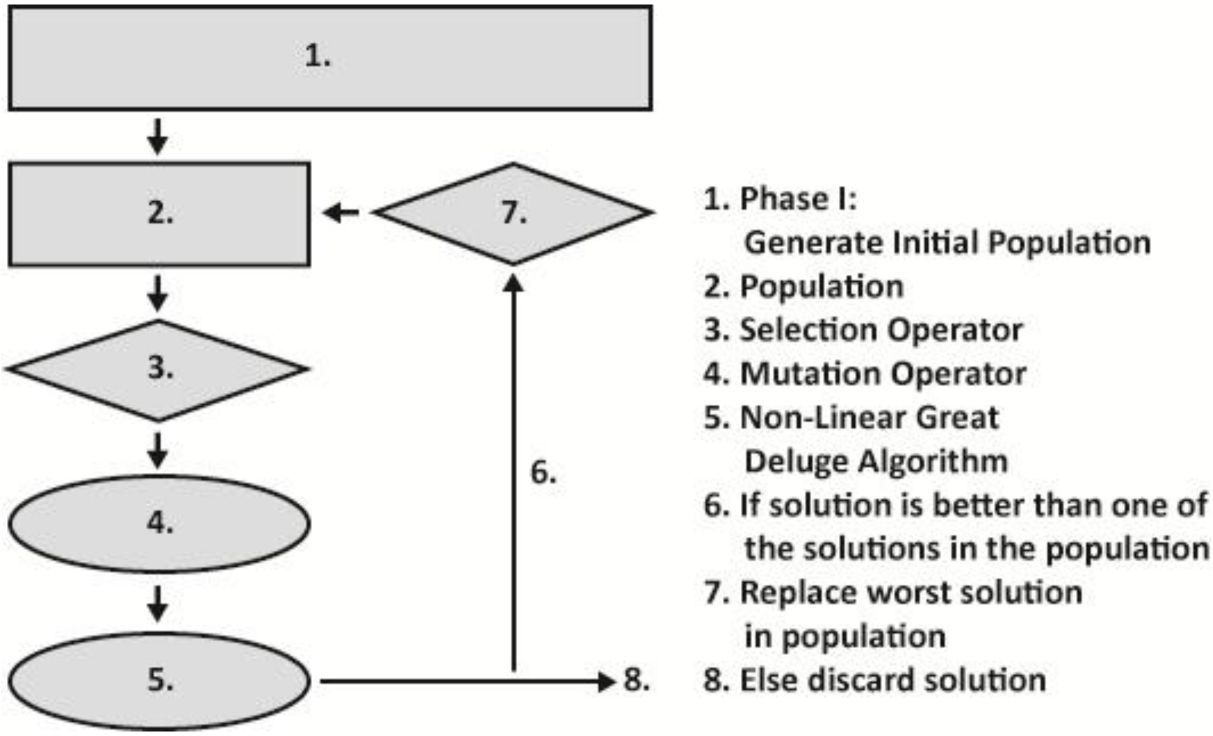


Figure 7: Hybrid Evolutionary Algorithm

7.3.2 THE POPULATION

Every genetic algorithm builds upon generations of solutions. The generations can evolve in two different ways which gives us two different kinds of genetic algorithms: the generational GA and the steady-state or incremental GA. A generational GA creates solutions for a new generation by performing mutation, recombination or other genetic operators to and with the members of the current generation. These new solutions are then put in a selection pool, and from this selection pool members are selected to form the new generation. From one generation to the next, all or nearly all members are replaced with new ones. Contrary to this, in a steady-state GA a new generation is created by replacing one or a few members of the generation by newly created solutions. Which solutions will be replaced is dictated by a replacement strategy, such as 'replace the oldest member' or 'replace the weakest member'.

As can be seen on figure 7 my algorithm is a steady-state algorithm. I also experimented with a generational algorithm but this didn't give fulfilling results. Given the time limit the algorithm could only produce a few generations, and a lot of effort was put into taking rosters of the same quality and doing basically the same local search on them. The diversity of the populations also dropped quickly. Although these problems could be tackled with adjusted methods, I decided to go further with a **steady-state evolutionary algorithm** with a **replacement strategy** of 'replace the weakest member'.

7.3.3 SELECTION OPERATOR

The selection operator used is a Roulette Wheel (RW) selection operator. With this type of selection every member of the population, also called chromosome, is given a chance to be selected based on their fitness. It is thus a stochastic selection process. The best timetable has the biggest chance to get selected. Figure 8 shows the logic behind the roulette wheel selection.

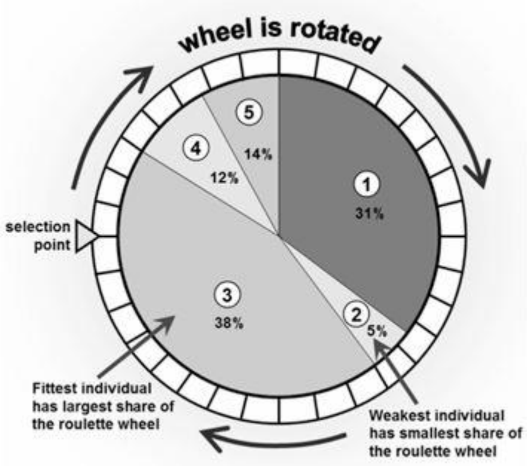

wheel is rotated
5
14%
4
12%
1
31%
selection point
3
38%
2
5%
Fittest individual has largest share of the roulette wheel
Weakest individual has smallest share of the roulette wheel

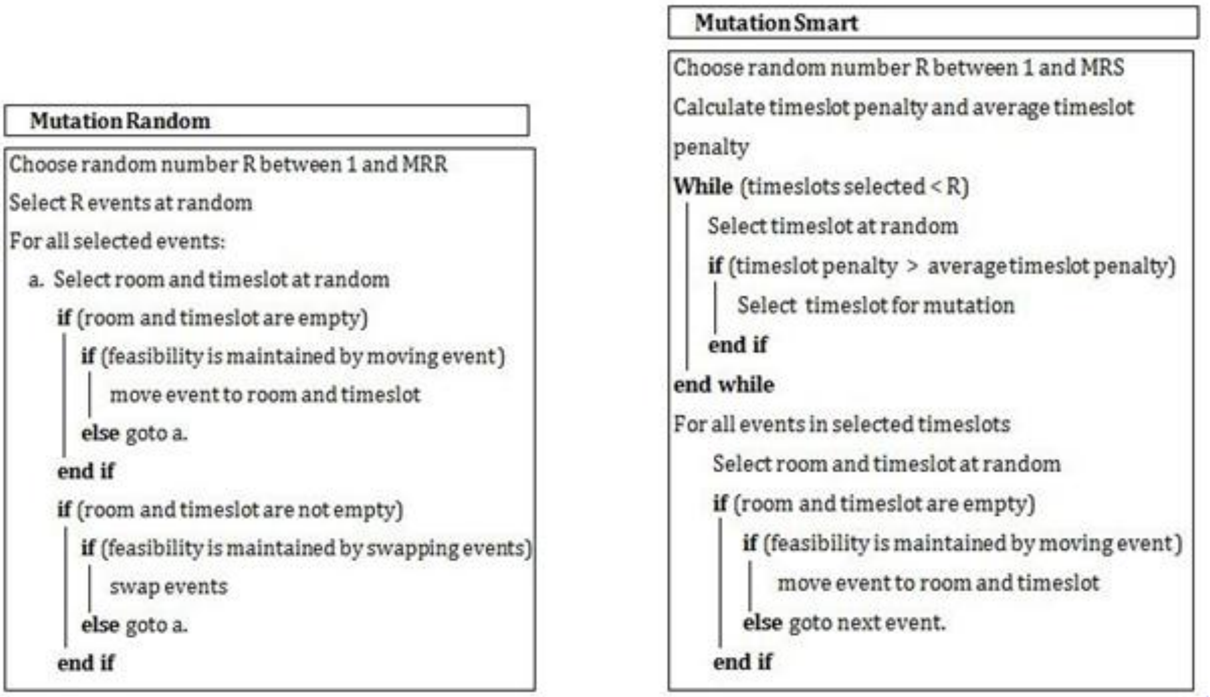
Figure 8: Roulette Wheel Selection

Each time the operator is executed the selection probability of each chromosome is recalculated, as this probability might have changed by the introduction of an improved solution in the population. I have chosen this selection operator based on a paper of Chinnasri and Sureerattanan (2010) in which they compare the performance of three selection operators: roulette wheel, rank based, and tournament selection, in genetic algorithms for university course timetabling problems. Their conclusion is that roulette wheel selection works more efficient when dealing with time constraints.

7.3.4 MUTATION OPERATORS

Two mutation operators are tested on the algorithm, a random and a smart mutation. M**utation Random** (MR) selects between zero and a certain number of events at random and moves them to another timeslot, while ensuring that feasibility is maintained. If the selected timeslot already has an event scheduled, the two events are swapped, if feasibility is maintained, otherwise another timeslot is selected. The exact number of events is indicated by the Mutation Rate Random (MRR). The optimal level for this rate will be tested in section 8. **Mutation Smart** (MS) selects between zero and a certain number of timeslots. The number is now indicated by the Mutation Rate Smart (MRS). The timeslots are only selected if the penalty arising from that timeslot (thus the penalty arising from the events scheduled in that timeslot) is higher than the average 'timeslot penalty'. When the right amount of timeslots is selected, the events scheduled in them are moved to empty locations in the timetable, while ensuring feasibility is maintained. If no feasible empty location is found, the event is not mutated. The pseudo-code of the MR and MS can be found in figure 9. One of them, or both, or none are applied to the selected solutions with a certain probability. In section 8 the results of assessing this probability will be shown.

I deliberately did not use any crossover operators, as is usual in a genetic algorithm. Every time a crossover would be executed, a 'repair function' to make the timetable feasible again would be needed. This can be very expensive in terms of cpu-time. A trade-off then has to be made between the expense and the advantage of using crossovers. I decided therefor to focus on varied mutation and a strong local search algorithm. Several authors also question the advantage of crossovers in timetabling (Lewis and Paechter, 2005; Burke et al., 1996). Lewis and Paechter (2004) performed a study of four different crossover operators for the timetabling problem, but they concluded that the results obtained with the operators were not state-of-the-art.



```
Mutation Random
Choose random number R between 1 and MRR
Select R events at random
For all selected events:
  a. Select room and timeslot at random
     if (room and timeslot are empty)
        if (feasibility is maintained by moving event)
           move event to room and timeslot
        else goto a.
     end if
     if (room and timeslot are not empty)
        if (feasibility is maintained by swapping events)
           swap events
        else goto a.
     end if
```

```
Mutation Smart
Choose random number R between 1 and MRS
Calculate timeslot penalty and average timeslot
penalty
While (timeslots selected < R)
   Select timeslot at random
   if (timeslot penalty > average timeslot penalty)
      Select timeslot for mutation
   end if
end while
For all events in selected timeslots
   Select room and timeslot at random
   if (room and timeslot are empty)
      if (feasibility is maintained by moving event)
         move event to room and timeslot
      else goto next event.
   end if
```

Figure 9: Pseudo-Code Mutation Random and Mutation Smart

7.3.5 NON-LINEAR GREAT DELUGE ALGORITHM

The local search operator used in the EA is a Non-Linear Great Deluge Algorithm. There are several reasons why I chose this specific method.

First I looked at the algorithm of the competition winner Kostuch. He works with a three-phase approach. The first phase constructs a feasible timetable, while trying to put the least events possible in the end-of-day timeslots. This is done by only opening these five timeslots for the events that remain unscheduled after several attempts of scheduling, shuffling and improvement. The next two phases try changing the sequence of timeslots, and exchanging pairs of events with a SA algorithm.

In section 6.2., p. 24, I mentioned the relatively new Great Deluge Algorithm. Its logic is very similar to that of SA, but according to Dueck (1993) it often outperforms SA. The GDA works with a parameter 'water level: B'. A solution is chosen at random from a neighborhood and is accepted if its objective function value is less than the current water level. In the original GDA the level of B is decreased monotonically (the similarity with SA is found in water level B <-> Temperature T). The algorithm converges when the water level outruns the current solution. This means that the water level is decreased so much that the algorithm cannot find a move anymore that reduces the Objective Function Value (OFV) such an amount that it would be lower than the water level.

Burke et al. (2003) compare the performance of SA with GDA on the twenty test instances of the ITC 2003 datasets. To prevent premature convergence their algorithm also accepts solutions if their objective function value is less than that of the current solution (the original GDA only accepts solutions that are better than the water level). Generally their experiments show that the GDA gives better results compared to SA. Figure 10 shows the results of SA (left side) and GDA on test instance 3 within a predefined time limit. The y-axis indicates the OFV, the x-axis indicates time and total moves, both on another scale.

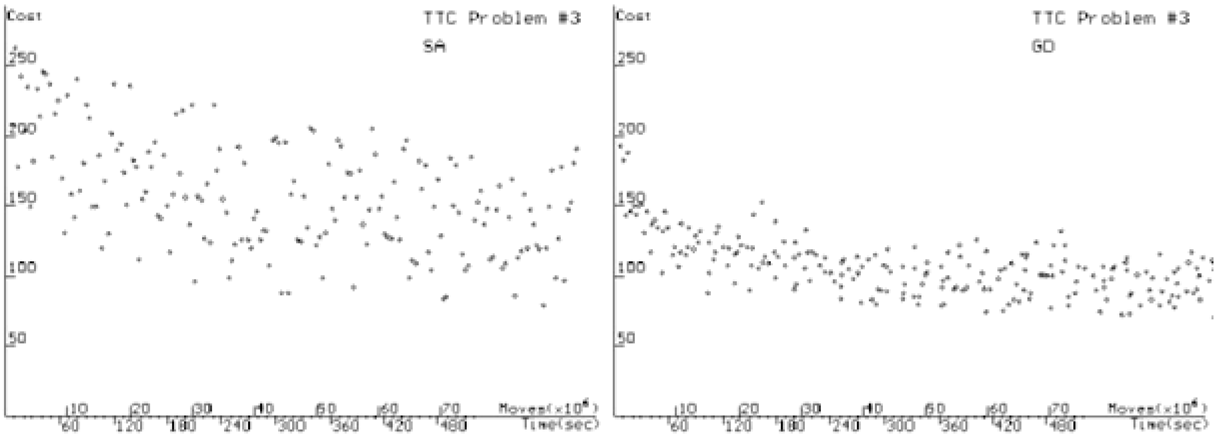


Figure 10: Comparison SA and GDA (Burke et al., 2003)

In 2008 a further improvement of the GDA used by Burke et al. was proposed by Obit and Landa-Silva. Instead of a linear decay rate of the water level (i.e. the speed at which B decreases), as in the algorithms of Dueck and Burke et al. (expression 1), they propose a non-linear decay rate of the water level as shown in expression 2.

Linear decay rate: $B = B - \Delta B$ (1)

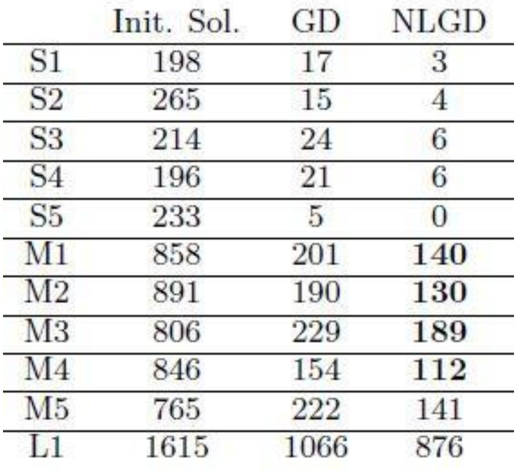
Non-linear decay rate: $B = B \times (\exp^{-\partial(\text{rand}[\min, \max])}) + \beta$ (2)

The parameters in expression 2 control the speed and the shape of the water level decay rate. Together they determine how fast the water level goes down. If it goes down really fast, improvement is achieved quickly, but the chance of getting stuck in local optima also increases. The results of fine-tuning the decay rate parameters will be described in the next section.

Another difference besides the non-linear decay rate, in the improved GDA of Obit and Landa-Silva, is the fact that they allow the water level to go up when its value tends to outrun the objective function value of the candidate solutions. The water level is then raised with a random number between B_{min} and B_{max}. The authors suggest a range of [1,3] for these values.

The neighborhoods used were **N$_1$**: select one event at random and move it to a feasible timeslot and room, **N$_2$**: swap two events randomly while feasibility is maintained, and **N$_3$**: select one event that causes a SCV and move it to a feasible timeslot and room.

They tested the algorithm on the problem instances of Socha et al. (2002) and compared the performance of the two decay rates. As can be seen from their results, shown in figure 11, the Non-Linear Great Deluge (NLGD) outperforms the Linear Great Deluge (GD) for every instance. Init. Sol. Indicates the objective function value of the initial solution.



	Init. Sol.	GD	NLGD
S1	198	17	3
S2	265	15	4
S3	214	24	6
S4	196	21	6
S5	233	5	0
M1	858	201	**140**
M2	891	190	**130**
M3	806	229	**189**
M4	846	154	**112**
M5	765	222	141
L1	1615	1066	876

Figure 11: Performance Non-Linear Great Deluge (Obit and Landa-Silva, 2008)

This brings us back to my algorithm. I used the NLGDA as proposed by Obit and Landa-Silva and tried to improve it by adding two neighborhoods:

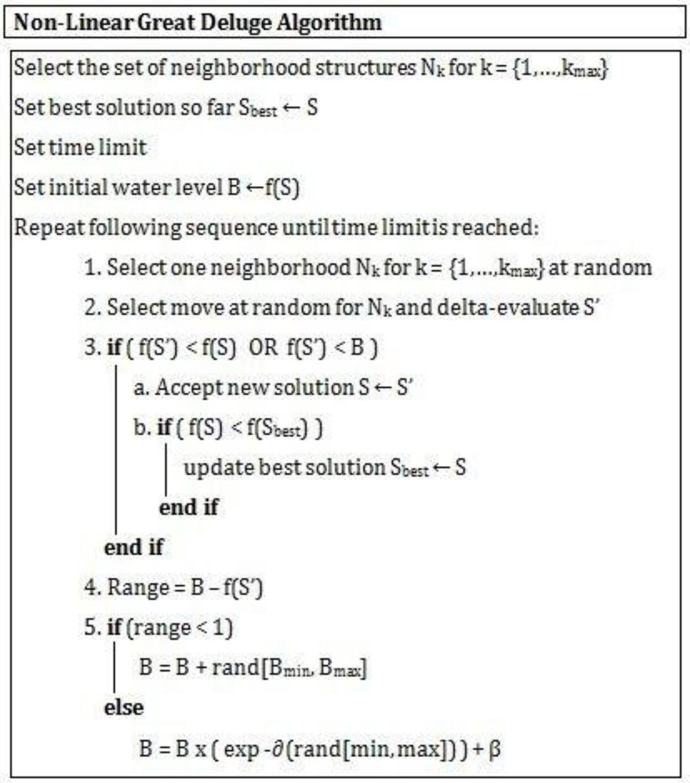
- **N$_4$**: Select two timeslots and swap all events scheduled in those timeslots.

This neighborhood is used in many papers, for example by Abdullah et al. (2007b). The advantages are that many events are exchanged at once. So in some cases this can improve the objective function value with a great amount. Feasibility is never lost since the grouping of events in the different timeslots isn't changed. Events that are scheduled at the same moment, will still be scheduled together after the timeslots are swapped. Because it changes the sequence of events this neighborhood will mainly improve the soft constraint violations caused by SC 2: a student having more than two consecutive classes and SC 3: a student having only one class in a day. It is less likely to improve the violations caused by SC 1: a student having an event in the last timeslot of the day. The penalty arising from this constraint will only decrease if one of the two timeslots exchanged is an end-of-day timeslot and if the other timeslot has very few events in it, or events taken by very few students.

- **N_5:** Select one event scheduled in an end-of-day timeslot and move it to a feasible room and timeslot (that is not in the end of the day)

This neighborhood has not been extensively studied in the literature, or at least I didn't find a paper that describes it. The perfect solution of the timetabling problem at hand has no events scheduled in any of the last timeslots. Therefor I wanted to test the effect of using a neighborhood that focuses on clearing up these timeslots. Obviously this neighborhood mainly reduces violations of SC 1.

The effect of these two extra neighborhoods will be tested in the next section. The complete pseudo code of the NLGDA is shown in figure 12.



```
Non-Linear Great Deluge Algorithm
Select the set of neighborhood structures $N_k$ for $k = \{1,\ldots,k_{max}\}$
Set best solution so far $S_{best} \leftarrow S$
Set time limit
Set initial water level $B \leftarrow f(S)$
Repeat following sequence until time limit is reached:
        1. Select one neighborhood $N_k$ for $k = \{1,\ldots,k_{max}\}$ at random
        2. Select move at random for $N_k$ and delta-evaluate $S'$
        3. if ( $f(S') < f(S)$  OR  $f(S') < B$ )
            a. Accept new solution $S \leftarrow S'$
            b. if ( $f(S) < f(S_{best})$ )
                update best solution $S_{best} \leftarrow S$
               end if
          end if
        4. Range = $B - f(S')$
        5. if (range < 1)
            $B = B + \text{rand}[B_{min}, B_{max}]$
          else
            $B = B \times (\exp -\partial(\text{rand}[\min, \max])) + \beta$
```

Figure 12: Pseudo-Code Non Linear Great Deluge

8. TEST DESIGN AND EXPERIMENTAL RESULTS

In this section different variations of the eventual algorithm will be tested. First the parameters and neighborhood use of the NLGDA, and once that is fine-tuned I will try to optimize the hybrid evolutionary algorithm. Please note that the experiments with the parameters are not exhaustive. Every parameter can be set to many different values, and moreover, combinations of various values of parameters can give different results. The correlation between the values of the parameters are usually not at all obvious or easy to trace. I therefore tried to test those values that seemed most promising and most logical. During the tests I always stayed aware of the fact that my final algorithm will have to be run within a given time limit. This time limit is indicated by a program that benchmarks your computer[1]. The output in my case is shown beneath, so I can run my algorithm for 636 seconds.

```
This program is running, please wait

This program took 106 seconds to run on your machine
This means that you can run your algorithm on the instances provided for 636 seconds

Press return to continue
```

8.1 LOCAL SEARCH PARAMETER TESTING

8.1.1 NEIGHBORHOODS

As described in section 7.3.5., p. 43, I added two extra neighborhoods in addition to the three neighborhoods proposed by Obit and Landa-Silva. To test the optimal combination of neighborhoods I first ran the NLGDA ten times for each of the combinations shown in table 11. The runtime was 100 seconds. This is not particularly long, but in the light of the time limit this is definitely long enough. In the eventual algorithm the runtime will most likely be much shorter. The left side of the table shows the average and the minimum SCV out of ten runs. The search started each time from a feasible

[1] This benchmark program can be downloaded from:
http://www.idsia.ch/Files/ttcomp2002/IC_Problem/node5.html

timetable constructed by the IH. The right side of the table shows the same results but sorted from small to large average SCV. The last column shows the increase in SCV's compared to the previous combination.

Neighborhood Combination	Average SCV (10)	Minimum SCV (10)
1-2-3	389,8	377
1-2-3-4	424,2	412
1-2-3-5	337,1	321
1-2-3-4-5	344	321
1-3-4-5	358,1	338
1-3-4	455,7	415
1-3-5	340,5	325
2-3-4	412,3	381
2-3-5	315,7	301
2-3-4-5	349,7	335

→

Neighborhood Combination	Average SCV (10)	Difference with previous
2-3-5	315,7	/
1-2-3-5	337,1	21,4
1-3-5	340,5	3,4
1-2-3-4-5	344	3,5
2-3-4-5	349,7	5,7
1-3-4-5	358,1	8,4
1-2-3	389,8	31,7
2-3-4	412,3	22,5
1-2-3-4	424,2	11,9
1-3-4	455,7	31,5

Table 11: Soft Constraint Violations of Different Neighborhood Combinations

This gives us a first impression of the performance of the neighborhoods. The first few combinations on the right side score best at this moment. To better see the impact of every specific neighborhood the following tables show the effect of adding N_1, N_2, N_4 or N_5. I did not test the effect of N_3 as this is the only neighborhood that swaps events pairwise. Deleting this neighborhood would limit the possibilities of the algorithm significantly so it is used in every test.

IMPROVEMENT OF N1 (= unclear)		
Neighborhood Combination	**Average SCV (10)**	**Difference**
2-3-4	412,3	
1-2-3-4	424,2	**-11,9**
2-3-5	315,7	
1-2-3-5	337,1	**-21,4**
2-3-4-5	349,7	
1-2-3-4-5	344	**5,7**

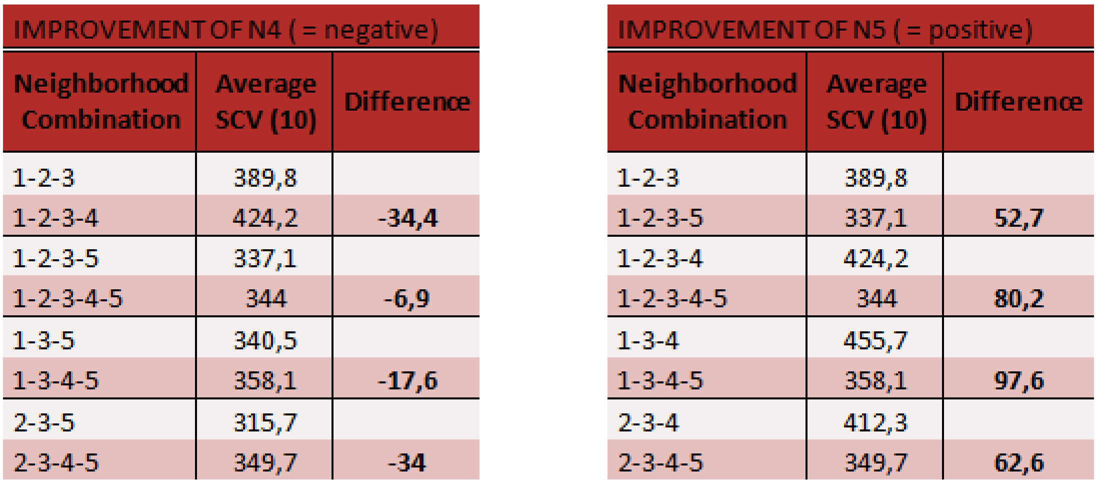
IMPROVEMENT OF N2 (= positive)		
Neighborhood Combination	**Average SCV (10)**	**Difference**
1-3-4	455,7	
1-2-3-4	424,2	**31,5**
1-3-5	340,5	
1-2-3-5	337,1	**3,4**
1-3-4-5	358,1	
1-2-3-4-5	344	**14,1**

Table 12: Assessment of Performance of Neighborhood One and Two

Table 12 shows the effect of adding N_1 and N_2 to different combinations. The effect of adding $\mathbf{N_1}$ is ambiguous. The difference between N_1 and N_2 is that N_2 only selects events that are violating a soft constraint, while N_1 selects events randomly. So without N_1 the algorithm selects events more efficiently. However, in the long run, or when the objective function value is already very low, only selecting events with SCV's might limit the flexibility of the search.

The effect of **N_2** is overall positive. This can be understood by the fact that it increases the efficiency of the search by selecting events with SCV's every time. N_1 and N_2 are the only neighborhoods that select events from all over the timetable and move them to an empty place. So, it will be best to use at least one of them. The choice then obviously goes to N_2. Whether we will also use N_1 and thus incorporate both of them will have to be decided based on further testing.

The outcomes of adding **N_4** and N_5 (the neighborhoods I added to the original ones of Obit and Landa-Silva) are shown in the table 13. Although the logic behind N_4 seemed reasonable, this neighborhood has a negative effect. I now assume that adding it slows down the search and thus leads to inferior results. Taking a closer look at the output of the search shows why. If we look at combination 1-2-3-4 we see that, for one run of 100 seconds, N_4 finds only 59 moves that reduce the OFV from the 3378 times it is selected. The other neighborhoods find 462, 547 and 668 moves out of 3232, 3244, and 3360 neighborhood selections respectively. This proves that N_4 indeed slows down the search. If we look back at table 11, we see that the fourth best combination is the one where all neighborhoods are used. It is obvious now that this is only so because of the strength of N_1, N_2, N_3, and N_5. N_4 will thus not be used as a neighborhood in our search algorithm.



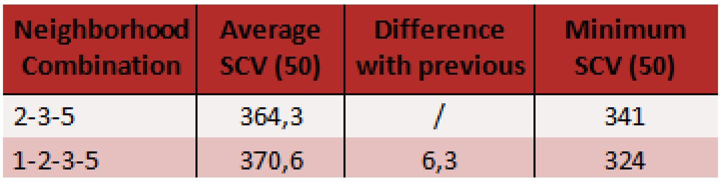
IMPROVEMENT OF N4 (= negative)		
Neighborhood Combination	Average SCV (10)	Difference
1-2-3	389,8	
1-2-3-4	424,2	**-34,4**
1-2-3-5	337,1	
1-2-3-4-5	344	**-6,9**
1-3-5	340,5	
1-3-4-5	358,1	**-17,6**
2-3-5	315,7	
2-3-4-5	349,7	**-34**

IMPROVEMENT OF N5 (= positive)		
Neighborhood Combination	Average SCV (10)	Difference
1-2-3	389,8	
1-2-3-5	337,1	**52,7**
1-2-3-4	424,2	
1-2-3-4-5	344	**80,2**
1-3-4	455,7	
1-3-4-5	358,1	**97,6**
2-3-4	412,3	
2-3-4-5	349,7	**62,6**

Table 13: Assessment of Performance of Neighborhood Four and Five

Finally we look at the effects of adding **N_5**. The results are clearly positive. N_5 focuses on emptying the last timeslots. Since every event that is scheduled in an end-of-day timeslot causes a SCV multiplied by the number of students taking the event, clearing up these timeslots pays off. Note that N_5 should always be used in combination with a neighborhood N_1 or N_2. If not, events would be placed out of the end-of-day timeslots, but couldn't be placed back in. This would cause the search to get stuck in a local optimum very quickly.

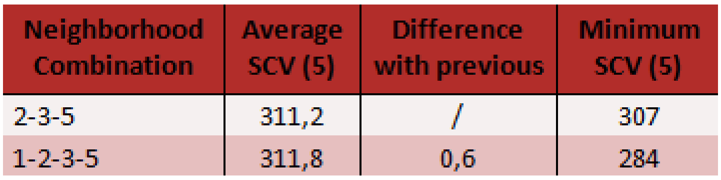
So this leaves us with two possibilities: the combination 1-2-3-5 or 2-3-5. To test this I first ran each of them fifty times, for 45 seconds. The results are shown in table 14. Combination 2-3-5 scores slightly better, but the results are not really significant.



Neighborhood Combination	Average SCV (50)	Difference with previous	Minimum SCV (50)
2-3-5	364,3	/	341
1-2-3-5	370,6	6,3	324

Table 14: Comparison of Performance of Best Neighborhood Combinations – 45 Seconds

Next I tested each combination five times, but now with a runtime of 500 seconds. I increased the runtime to see the performance of the neighborhoods when the objective function value is already relatively low. This is very important because the main goal is of course to get the objective function value as low as possible.



Neighborhood Combination	Average SCV (5)	Difference with previous	Minimum SCV (5)
2-3-5	311,2	/	307
1-2-3-5	311,8	0,6	284

Table 15: Comparison of Performance of Best Neighborhood Combinations – 500 Seconds

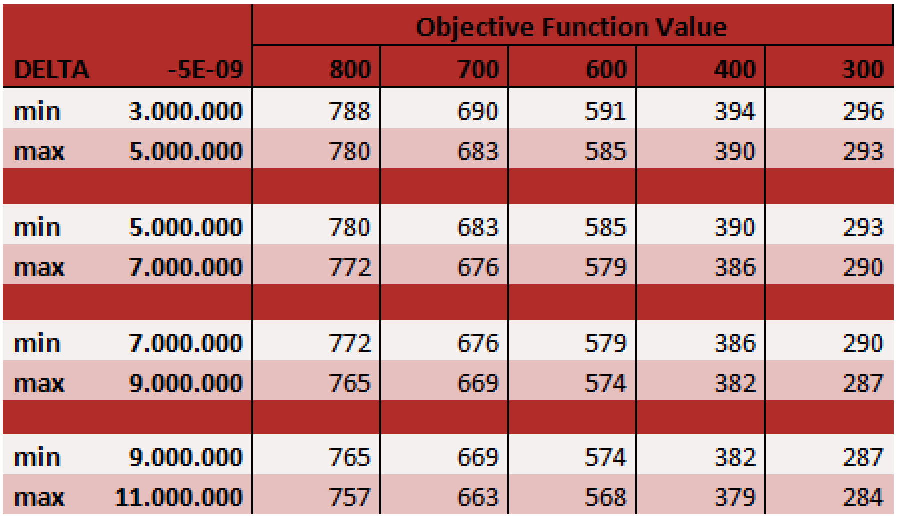
Now the difference between the two is even less. I therefor decide to use the second combination, namely N_1, N_2, N_3, and N_5 for my final algorithm. The addition of N_1 is certainly not negative, and towards the end it will make the search trajectory more flexible.

Finally I checked if there was no skew in the selection of the neighborhoods during the search, as this would seriously affect the outcomes and corrupt the results of the previous tests. Luckily this was not the case. In a test were the runtime was set to 1000 and all neighborhoods were used the total times of selection per neighborhood was:

36.064 + 35.934 + 35.604 + 35.810 + 35.951 with a total of 179.363.

8.1.2 DECAY RATE PARAMETERS

All previous tests were executed with the same values for the parameters of the decay rate: B = B x (exp$^{-\partial(\text{rand}[\text{min},\ \text{max}])}$) + β. B stands for the minimum expected objective function value. The twenty instances of the ITC all have at least one perfect solution, so β is set to zero. The others were set to: 5 x 10^-9 for delta, 5.000.000 for min and 7.000.000 for max. The value of delta is proposed by Obit and Landa-Silva for large instances. I will therefore keep delta at this value. For min and max they propose to use 100.000 and 300.000, which is significantly lower than the values I used. In their paper however they set the runtime of their algorithm to 6700 seconds for large instances which is very high, and far above the maximum runtime for my complete algorithm. I therefore decided that it would be best to set my min and max values a lot higher. This indeed increases the chance of getting stuck in a local optimum. But, I will implement the search algorithm within an evolutionary algorithm where the mutation operators are meant to escape from local optima. In the evolutionary algorithm, the NLGDA will run a very short period every time it is executed. Therefore, to obtain good results, the min and max values should be set sufficiently high so that significant improvement can be reached within the runtime of each search. To make the decay rate expression less abstract I calculated the outcomes of it for several parameters and several objective function values. The values in table 16 indicate to which level the water level is decreased every time an improvement is found.



		Objective Function Value				
DELTA	-5E-09	800	700	600	400	300
min	3.000.000	788	690	591	394	296
max	5.000.000	780	683	585	390	293
min	5.000.000	780	683	585	390	293
max	7.000.000	772	676	579	386	290
min	7.000.000	772	676	579	386	290
max	9.000.000	765	669	574	382	287
min	9.000.000	765	669	574	382	287
max	11.000.000	757	663	568	379	284

Table 16: Values of Water Level with Different Parameters

So if we look at the upper right corner for instance, if an OFV is found that is below 300, let's say 294, then the water level decreases to a value somewhere between 293 and 296, let's say 296. The next search a move is accepted if the OFV of that move is less than 294 (the current OFV) or less than 296 (the current water level). If the move has an OFV of more than those values, it is not accepted, and the water level is raised with a value between 1 and 3. Recall that the algorithm allows the water level to go up with a value between B_{min} and B_{max} (see pseudo code p. 44). Obit and Landa-Silva suggest a range of [1, 3], and I will also use these values. I also did some preliminary tests with a range [2, 4]. The water level fluctuated much more than with [1, 3], but it didn't lead to better results. Figure 13 and 14 show the graphs of the search trajectory with range [1, 3] and [2, 4] respectively. The x-axis shows the CPU-time in seconds. We can see that in the first graph the water level gradually guides the OFV to lower levels, while in the second graphs the water level fluctuates around the OFV and often drops below it. Only the first two seconds of the search are depicted, so these graphs are not meant to draw conclusions, they are only illustrative for the effect of the range with which the water level is increased. The final OFV is the minimal value reached after 500 seconds.

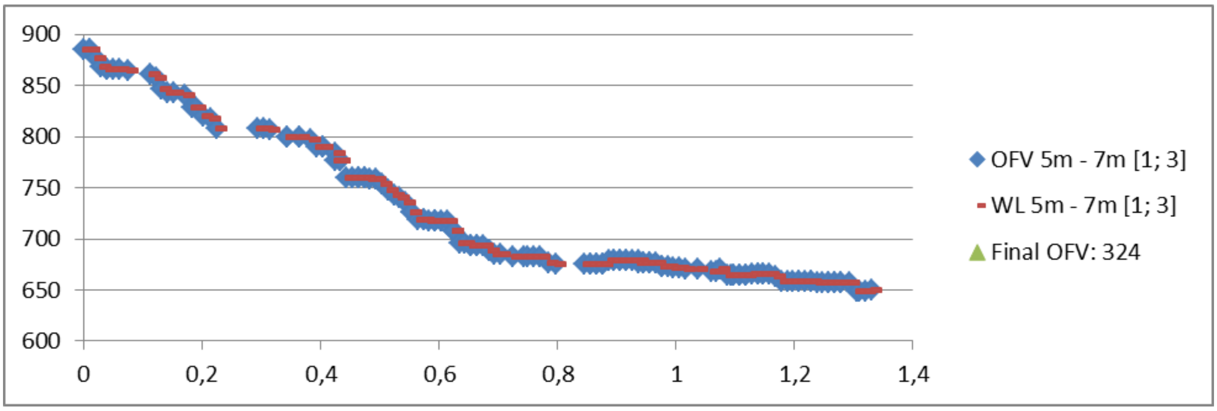


Figure 13: Objective Function Value and Water Level Decay for Range [1; 3]

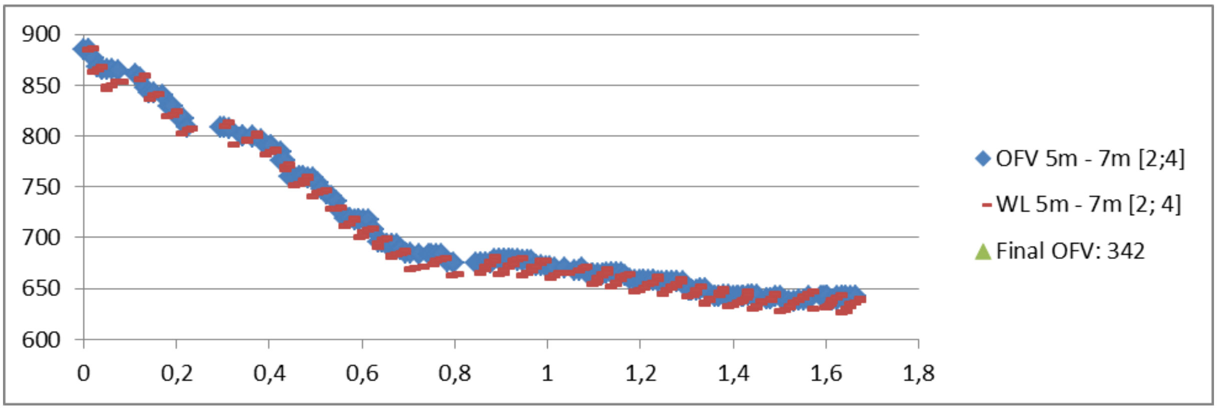


Figure 14: Objective Function Value and Water Level Decay for Range [2; 4]

The next graph, figure 15 shows the proceedings of the search, for three different ranges of min and max, as indicated in the legend. Again the x-axis shows the CPU-time in seconds. The graph only shows the best OFV found within that time. So these are not the same kind of data as the two graphs showed above with the water level where every OFV is indicated. As I explained before, the higher the min and max values, the faster the search finds improvements. Indeed, the interval [7.000.000, 9.000.000] finds the lowest OFV, and has the steepest curve. However, these results should be interpreted carefully. They were obtained with a very high initial OFV. This will be very different when the NLGDA is used within the EA, and each search trajectory is started with low OFV's. I will therefore not draw conclusions here as to which min and max values I should use, but rather I will experiment with these values in the complete algorithm.

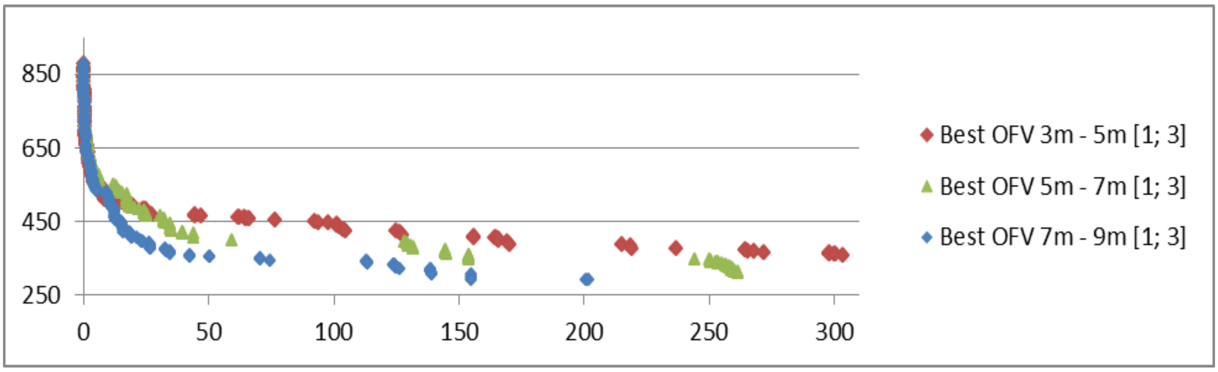


Figure 15: Best Objective Function Values for Different Min and Max Parameters

8.2 POPULATION PARAMETER TESTING

First I would like to recall that the parameter testing is absolutely not exhaustive. In this section I started with a certain combination, analysed the results from that combination and adjusted the values in a way I think could improve the algorithm. The logic behind this and the assumptions I made are explained hereunder for every test. I give a table indicating the values of all parameters, and the best results obtained, ordered from low to high values. Every test is run for 636 seconds, the maximum runtime for my laptop according to the competition benchmark. MR and MS Probability are the chance that a roster will be mutated by that mutation when it is selected from the population to run through the algorithm. Min and max is indicated in million (m). The values not indicated in the tables are: delta = 5 * 10^-9, B_{min} = 1, B_{max} = 3, and the neighborhood combination is 1-2-3-5.

Population Size	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	min	max	Best result
10	/	0	4	0,5	30s	7m	9m	280

Table 17: Parameter Combination 1

For the first test I started with a small population, with only Mutation Smart as mutation operator and the values for min and max that appeared to be the most promising in figure 15. I started with MRS of four. This means that every time the mutation was executed between zero and three timeslots were chosen and the events in them were rescheduled. I quickly noticed that this mutation rate was rather high. After the program was running a while and all rosters in the population had reached a low OFV the mutation rate caused that after a roster was mutated, its OFV sometimes raised with more than 150. To me this didn’t seem to be an optimal mutation. Also I noticed that the diversity of the population quickly dropped, as can be seen on the figure 16. This can be simply explained by the fact that with the roulette wheel the best chromosome has the most chance to be selected, and then, after it has run through the algorithm it replaces the worst roster in the population. So after a while many or all population member are a variant of the same roster.

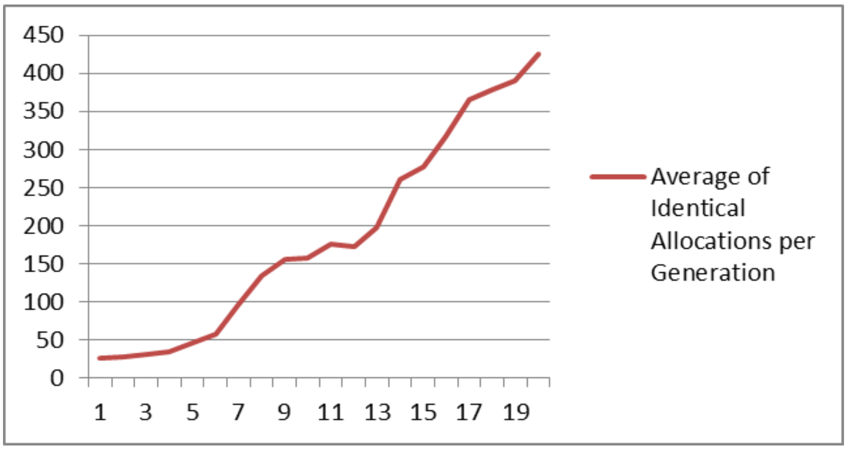
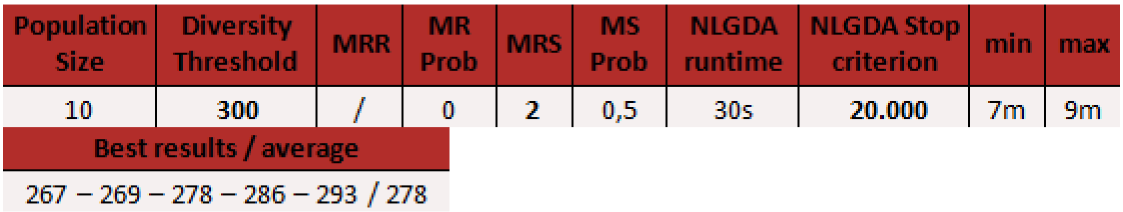


Figure 16: Diversity of Population Per Generation for Parameter Combination 1



Population Size	Diversity Threshold	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	NLGDA Stop criterion	min	max
10	**300**	/	0	**2**	0,5	30s	**20.000**	7m	9m

Best results / average
267 – 269 – 278 – 286 – 293 / 278

Table 18: Parameter Combination 2

For the next run I did quite a few adjustments. First, to prevent the diversity from declining I installed a diversity threshold acceptance criterion. This changes number six on the figure of the complete algorithm depicted on page 38. When a new solution is created first its diversity with the rosters in the population is calculated. If there is a roster in the population that has 300 or more identical allocations compared to the newly created roster, than only one of them is kept, namely the one with the smallest OFV. If there are no rosters with 300 or more identical allocations, than the newly created solution replaces the worst of the population. The level of the threshold can of course also be adjusted depending on the desired level of diversity. Next, I lowered the MRS to two since I assume that the previous higher MRS had a negative effect on the results. Also I included a second stop criterion for the NLGDA. Namely to stop after 20.000 neighborhood selections without an improvement. This number can also be adjusted and I based the 20.000 on the previous run where rarely an improvement was found after 20.000 selections without improvement. This way unfruitful runs of the local search are stopped before they reach 30 seconds and precious CPU-time is won. I ran the algorithm with these values four times, to better see whether the effects of the parameters are real are due to randomness.

The results show that the threshold criterion works as required. The diversity stays at very acceptable levels as shown in Figure 17. The threshold might appear to be set quite high, but the graph shows that the level of diversity stays very good, far below the threshold level. The NLGDA also has the desired effect as the algorithm can create about ten generations more (30 compared to 20). The graph doesn't actually have 30 generations but this is because when a newly created roster is too similar to a roster of the population and it has a lower OFV the population doesn't change so that doesn't count as a new generation. The lower mutation rate also seems to give better results.

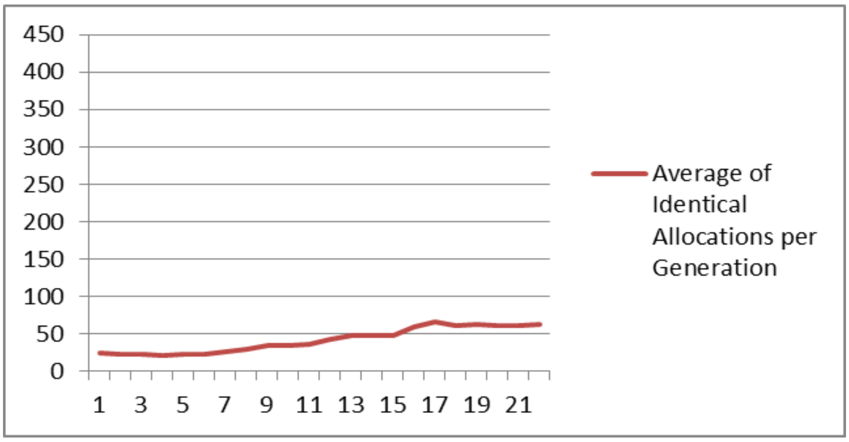


Figure 17: Diversity of Population Per Generation for Parameter Combination 2

Population Size	Diversity Threshold	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	NLGDA Stop criterion	min	max
10	300	**10**	**0.75**	**/**	**0**	**/**	**10.000**	7m	9m

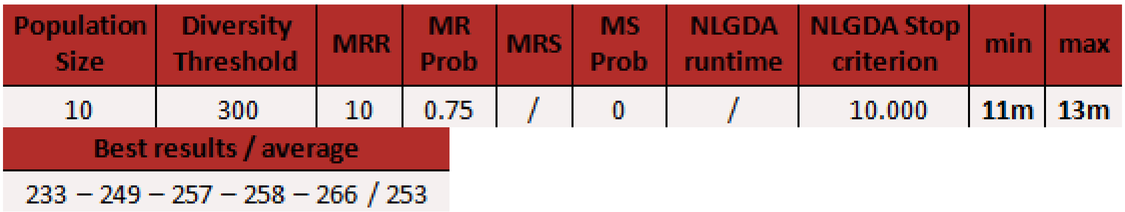
Best results / average
269 – 269 – 272 – 274 – 277 / 272

Table 19: Parameter Combination 3

Next I deleted the runtime stopping criterion for the NLGDA. With the neighbourhood stopping criterion installed it doesn't make sense to stop searches after a certain time if they are still finding improvements. I put the value to 10.000 neighborhood selections without improvement. I also quickly tested with 20.000 selections but this gave very poor results.

Also I tested the Mutation Random with an MRS of 10 instead of Mutation Smart. This mutation selects between zero and ten events and reschedules them. It is more levelled than Mutation Smart as this last selects either zero or ten events (maximum one timeslots was selected with MRS 2 and this usually has all rooms occupied so contains ten events). As the mutation will usually select less events I used a mutation probability of 0.75.

The results are slightly better, but not significant. Due to the changed stopping criterion of the local search, a lot more loops of the algorithm are executed. Although it didn't lead to better results here, this could be an advantage when other parameters are optimized.



Population Size	Diversity Threshold	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	NLGDA Stop criterion	min	max
10	300	10	0.75	/	0	/	10.000	**11m**	**13m**

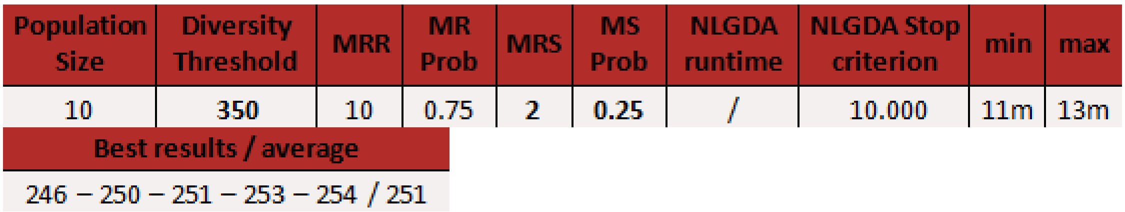
Best results / average
233 – 249 – 257 – 258 – 266 / 253

Table 20: Parameter Combination 4

Next, I increased the min and max values. As explained before this will cause that the search faster finds improvement, but has a higher chance to get stuck in local optima. I kept the other parameters unchanged to clearly see the results of the higher min and max values.

The results are visibly positive. With an average of twenty SCV's less we can assume this is not due to randomness. I would like to depict the effect of the higher min and max values on the local searches, but this is not so easy. The search trajectory sometimes doesn't find improvement at all, and in other runs a lot. So depicting one or a few of all the executions of the NLGDA wouldn't say very much, or enable us to thoroughly analyse why the higher values lead to better results.

If I look at the different outputs I see that a newly created roster very often replaces the old version of itself. This means that the rosters do not change a lot as they always exceed the diversity threshold. I am not sure whether this has a negative effect on the results. In a way it's normal that they do not change a lot. Only when a mutation opens the way to significant improvements the allocations will really differ. If the mutation changes some events in a way that only a small improvement can be found, most likely not a high percentage of the allocations will change.

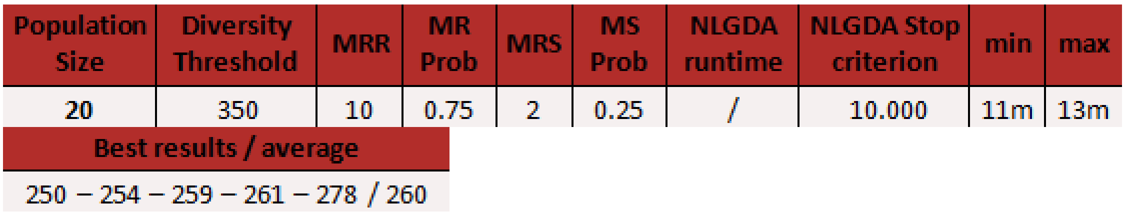


Population Size	Diversity Threshold	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	NLGDA Stop criterion	min	max
10	**350**	10	0.75	**2**	**0.25**	/	10.000	11m	13m
Best results / average									
246 – 250 – 251 – 253 – 254 / 251									

Table 21: Parameter Combination 5

For the next test I increased the diversity threshold to 350 because of the reason just explained. Also I start using Mutation Smart again, but with a low probability and with a MRS of two, meaning maximum one timeslot can be selected for mutation. Now every selected roster is selected for mutation, but there is still a chance no events are mutated as both mutation operators can select zero events.

The results are slightly better, but not significant. The fact that rosters usually replace themselves stayed the same. The average diversity in the population decreases a little bit but not so that the population isn't diverse enough anymore. With the threshold on 300 the diversity declined to a maximum of around 100 identical allocations, compared to 150 when the threshold is 350.

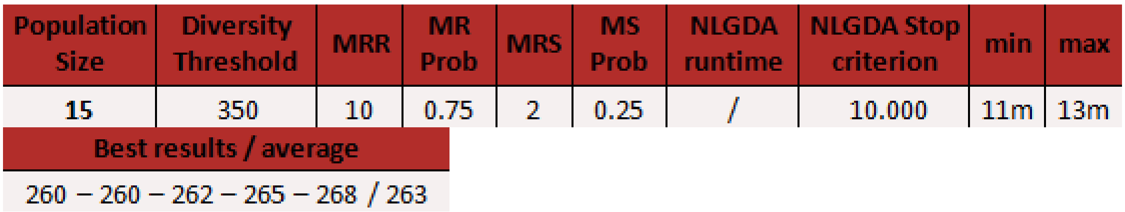


Population Size	Diversity Threshold	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	NLGDA Stop criterion	min	max
20	350	10	0.75	2	0.25	/	10.000	11m	13m
Best results / average									
250 – 254 – 259 – 261 – 278 / 260									

Table 22: Parameter Combination 6

For the next test I doubled the population size to twenty rosters. The idea is that as the population size is bigger, there are more rosters, which are all very different thanks to the diversity threshold criterion, and thus the chance that the population has a roster that might lead to very good results increases.

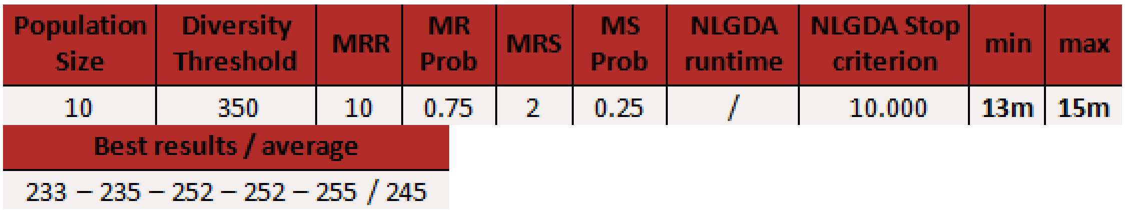
The results do not support this hypothesis. The average is about ten SCV's higher than before. So perhaps this population was too big.



Population Size	Diversity Threshold	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	NLGDA Stop criterion	min	max
15	350	10	0.75	2	0.25	/	10.000	11m	13m
Best results / average									
260 – 260 – 262 – 265 – 268 / 263									

Table 23: Parameter Combination 7

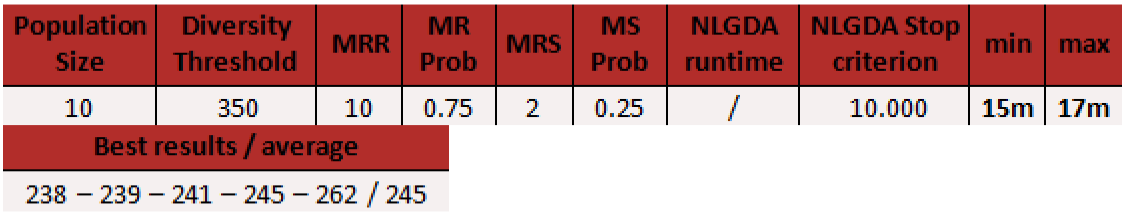
But also with a population size of fifteen the results do not improve. I assume now that as the population is bigger, each roster is selected for mutation and local search less often. So per individual there are fewer attempts to improve it, and so the results might be worse. More specific, with the current parameters there are about 40 to 50 generations created every time. With a population of twenty, on average every roster is only selected two times, while this is four times with a population of ten. I won't try to make the population even smaller. Ten individuals is already a rather small population and the strength of a diverse population, which is one of the main elements of an evolutionary algorithm, would be undermined.



Population Size	Diversity Threshold	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	NLGDA Stop criterion	min	max
10	350	10	0.75	2	0.25	/	10.000	**13m**	**15m**
Best results / average									
233 – 235 – 252 – 252 – 255 / 245									

Table 24: Parameter Combination 8

Having experimented with the population size, I further increase the min and max values, as this gave positive results last time. This seems to give positive results but the difference is not so big, compared with table 21: parameter combination 5 where the other value are the same.



Population Size	Diversity Threshold	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	NLGDA Stop criterion	min	max
10	350	10	0.75	2	0.25	/	10.000	**15m**	**17m**
Best results / average									
238 – 239 – 241 – 245 – 262 / 245									

Table 25: Parameter Combination 9

With even bigger min and max values the results stay more or less the same, so I assume that the positive effect of raising those values has reached its maximum now.

Population Size	Diversity Threshold	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	NLGDA Stop criterion	min	max
10	350	10	0.75	2	0.25	/	**5.000**	13m	15m

Best results / average
233 – 241 – 242 – 244 – 256 / 243

Table 26: Parameter Combination 10

For the next test I reset the min and max values to thirteen and fifteen million. From the outputs of the local searches of the previous tests (combination eight) I saw that improvements were usually found within 5.000 neighborhood selections, or even a lot less. More exactly, from 6.139 improvements made in the five runs together, only 65 were found after more than 5.000 neighborhood selections. So I now tested with a stop criterion of 5.000. This gives the algorithm the chance to create a lot more generations, and thus every roster is selected more often to run through the algorithm.

The results do not vary significantly, but they are definitely not worse. Recall the reason that I assumed that testing with a bigger population didn't pay off, namely that every roster is selected less times to run through the algorithm. However, with this sharper stop criterion for the local search, a lot more generations are created. About 100 compared to 50 before.

Population Size	Diversity Threshold	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	NLGDA Stop criterion	min	max
20	350	10	0.75	2	0.25	/	5.000	13m	15m

Best results / average
242 – 247 – 259 – 259 – 260 / 253

Table 27: Parameter Combination 11

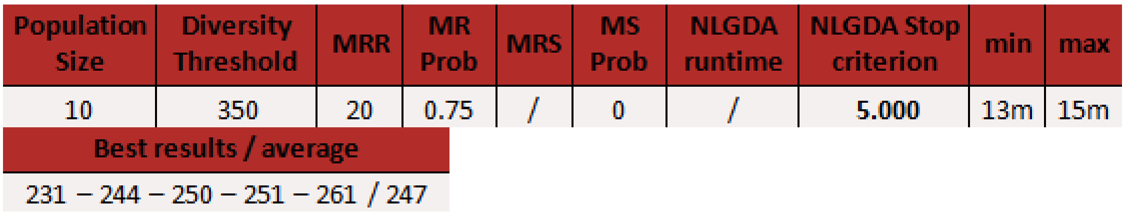
Population Size	Diversity Threshold	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	NLGDA Stop criterion	min	max
20	350	10	0.75	2	0.25	/	**3.000**	13m	15m

Best results / average
236 – 243 – 243 – 245 – 246 / 243

Table 28: Parameter Combination 12

So, once more I tried to assess the effect of increasing the population size. Once with a stop criterion of 5.000 and once with 3.000.

For 5.000 the results are definitely not better. For 3.000 they are more or less the same as the results with a population of 10 and a stop criterion of 5.000. I will decide which parameters (population 10 and stop criterion 5.000 or population 20 and stop criterion 3.000) to use for my final algorithm based on testing these two combinations on another instance of the competition (see infra, p. 60).

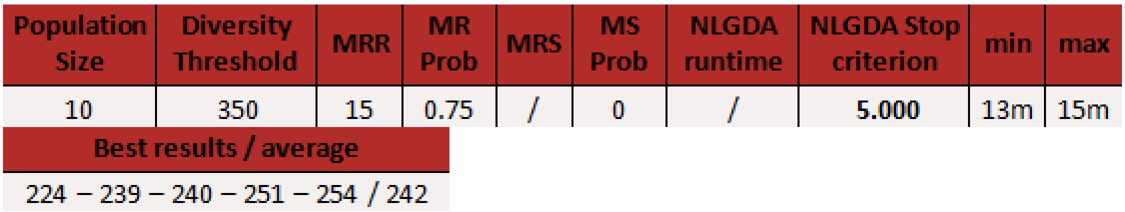


Population Size	Diversity Threshold	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	NLGDA Stop criterion	min	max
10	350	20	0.75	/	0	/	5.000	13m	15m
Best results / average									
231 – 244 – 250 – 251 – 261 / 247									

Table 29: Parameter Combination 13

Finally I set up some last test runs to try to optimize the parameters of the mutation operators. First I only used Mutation Random. I tried to increase the mutation rate quite a bit, to 20. So now between zero and nineteen events are selected. I kept the mutation probability at 0,75 because the rate is rather high.

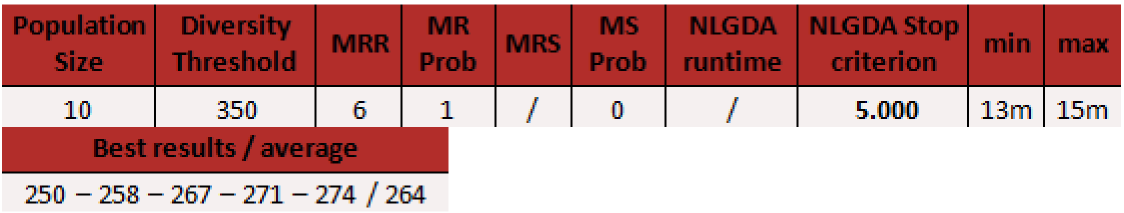
The results do not really show an improvement. So I assume that the MRR was set too high.



Population Size	Diversity Threshold	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	NLGDA Stop criterion	min	max
10	350	15	0.75	/	0	/	5.000	13m	15m
Best results / average									
224 – 239 – 240 – 251 – 254 / 242									

Table 30: Parameter Combination 14

Next I decreased the rate to fifteen. This also didn’t give better results. The average is significantly decreased by the outlier 224. I assume this is due to a particularly good random seed and local search proceedings, but is not the effect of the changed mutation parameters.

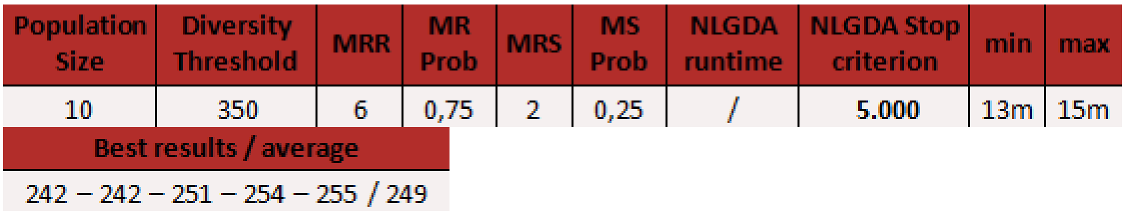


Population Size	Diversity Threshold	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	NLGDA Stop criterion	min	max
10	350	6	1	/	0	/	5.000	13m	15m
Best results / average									
250 – 258 – 267 – 271 – 274 / 264									

Table 31: Parameter Combination 15

The higher mutation rates didn't improve the outcomes so I tried to put the MRR relatively low. The mutation probability was now set to one to counterbalance the really low mutation rate.

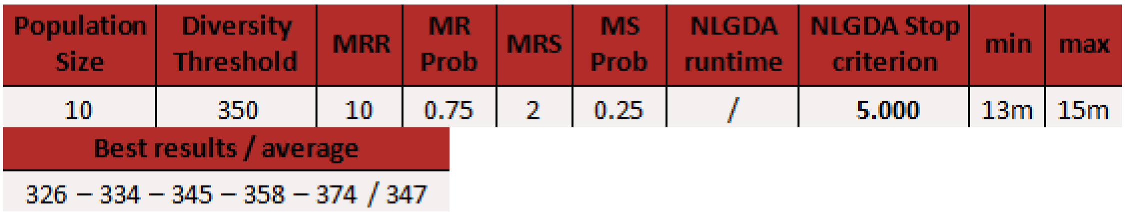
Again the results did not improve. I won't try to test with Mutation Smart as the only mutation as this is a rather inflexible mutation. The amount of events mutated is always zero, nine or ten, nineteen or twenty, … So I do not expect this will yield good results.



Population Size	Diversity Threshold	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	NLGDA Stop criterion	min	max
10	350	6	0,75	2	0,25	/	5.000	13m	15m
Best results / average									
242 – 242 – 251 – 254 – 255 / 249									

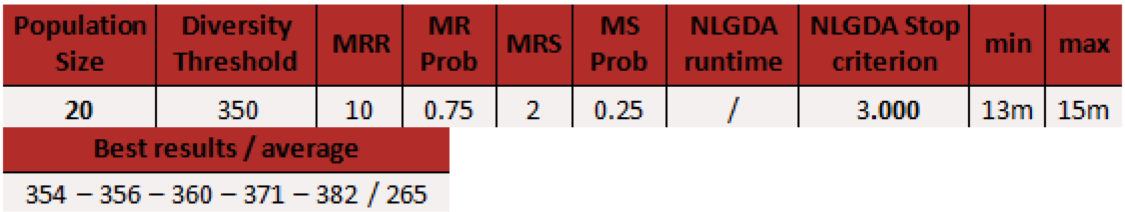
Table 32: Parameter Combination 16

I did one more test with both mutations where I lowered the MRR to six. But also this did not show better results. My conclusion of the mutation rate testing is that the combination of both mutations works best, with a higher probability for Mutation Random, and with MRR set to ten and MRS to two.



Population Size	Diversity Threshold	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	NLGDA Stop criterion	min	max
10	350	10	0.75	2	0.25	/	**5.000**	13m	15m
Best results / average									
326 – 334 – 345 – 358 – 374 / 347									

Table 33: Parameter Combination 17 – Instance 13

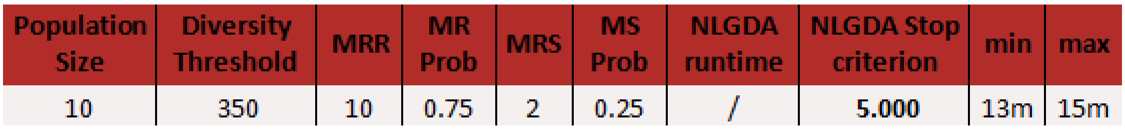


Population Size	Diversity Threshold	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	NLGDA Stop criterion	min	max
20	350	10	0.75	2	0.25	/	3.000	13m	15m
Best results / average									
354 – 356 – 360 – 371 – 382 / 265									

Table 34: Parameter Combination 18 – Instance 13

A final test that I ran is to see the difference between the two most promising combinations of parameters so far. I tested both of them on another instance of the competition, namely instance thirteen. There is no particular reason why I chose this instance, I could have chosen any other instance as the algorithm will have to work on all of them. The tables underneath show the results of five test runs. The first combination (17) is clearly outperforming the second (18).

The parameter testing lead to the following combination of values to which the parameters will be set in the final algorithm.



Population Size	Diversity Threshold	MRR	MR Prob	MRS	MS Prob	NLGDA runtime	NLGDA Stop criterion	min	max
10	350	10	0.75	2	0.25	/	**5.000**	13m	15m

Table 35: Final Parameter Settings

Two final remarks are in place here. First I would like to note that I did not incorporate different instances for the local search parameter testing nor the population parameter testing. Different instances would probably lead to different outcomes, but, as indicated by the competition rules, the same values have to be used to obtain the final results for all instances. It would be nearly impossible to set the parameters in such a way that they are optimal for all instances, and setting them to average levels would definitely not improve the final overall result. Thus I considered testing with one instance to be sufficient.

A second remark concerns the benchmark program of the competition. All competitors had to run this benchmark on their machine to know for how long they could run their algorithm per instance. At first I wanted to use two laptops for the parameter testing to speed up the process, so I ran the benchmark on both machines. I made sure no background processes were on, and that the power scheme was set to 'high performance'. For the first laptop the outcome was that I could run the algorithm for 528 seconds, for the second the outcome was 636 seconds. However when I ran the algorithm on both laptops for the same amount of time, the second always showed better results. This doesn't make sense as the first laptop should give better results when it runs the program for more than the time indicated it is allowed to run it. On the competition's website is said that if the outcome of the benchmark is not roughly around 500 seconds you should get in touch with the organisation. But I assume that for 528 and 636 seconds this would not be necessary.

Eventually I performed all tests on the second machine so normally this issue didn't influence my results. However, as the competition instances are commonly used by many researchers, it would be better if this benchmark worked correctly.

9. RESULTS

All the parameter testing finally brings us to the results. In this section I will show my final algorithm with its correct parameter settings, and the results obtained with it. I will also compare these results with the official results of the competition.

9.1 FINAL ALGORITHM

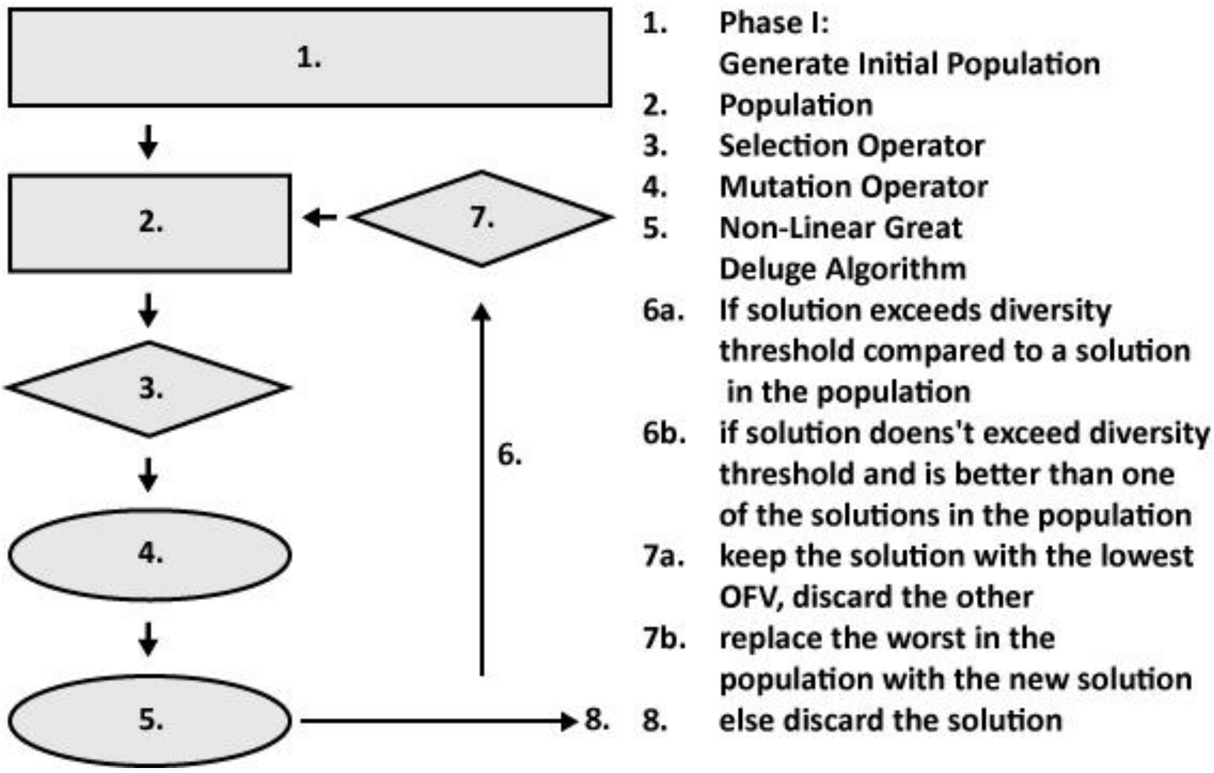

1.
2.
3.
4.
5.
6.
7.
8.
1. Phase I: Generate Initial Population
2. Population
3. Selection Operator
4. Mutation Operator
5. Non-Linear Great Deluge Algorithm
6a. If solution exceeds diversity threshold compared to a solution in the population
6b. if solution doens't exceed diversity threshold and is better than one of the solutions in the population
7a. keep the solution with the lowest OFV, discard the other
7b. replace the worst in the population with the new solution
8. else discard the solution

FIGURE 18: FINAL HYBRID EVOLUTIONARY ALGORITHM

The final algorithm is the same as the one explained in section 7.3.1 on page 38, but with a few adjustments.

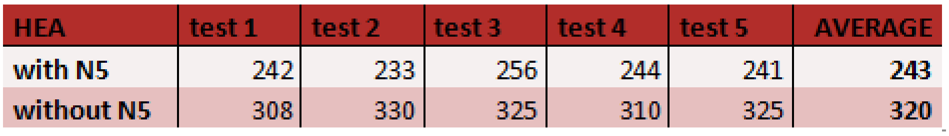
The **replacement strategy** now includes a diversity threshold criterion (which is set to 350 identical allocations) as shown on figure 18 under numbers six and seven. After the NLGDA the solution either follows six a) or six b). Depending on that it follows the same letter for number seven and eight.

The **population size** is ten. The population is created in the first phase with Initialisation Heuristic 3.

The **selection operator** is the roulette wheel selection. This works without any parameters.

The **mutation operators** used are both Mutation Random and Mutation Smart. 75 per cent of the rosters is selected for Mutation Random, and 25 per cent for Mutation Smart. MRR is set to ten, MRS to two.

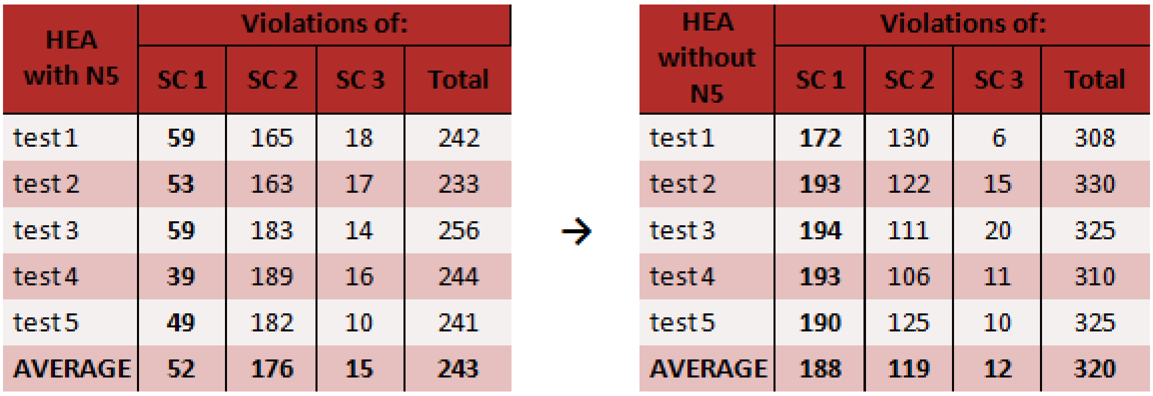
The **search operator** is the Non-Linear Great Deluge Algorithm. Every time it is executed it runs until it has selected 5.000 neighborhoods without finding an improvement of the OFV. The neighborhoods used are N_1, N_2, N_3, and N_5. N_5 is the neighborhood that I added to the neighborhoods proposed by Obit and Landa-Silva (2008). To recall how this neighborhood works, see section 7.3.5, p. 44. To assess the value of this neighborhood I compared the performance of my complete algorithm with N_5 and without N_5. The results are shown in table 37.



HEA	test 1	test 2	test 3	test 4	test 5	AVERAGE
with N5	242	233	256	244	241	**243**
without N5	308	330	325	310	325	**320**

Table 36: Comparison of Performance HEA with and without Neighborhood 5

The outcomes of the algorithm with or without N_5 differ significantly. I can confidently say that N_5 is a strong neighborhood that significantly increases the performance of the algorithm. Table 38 clarifies the big difference between the values in table 37.



HEA with N5	Violations of:			
	SC 1	SC 2	SC 3	Total
test 1	**59**	165	18	242
test 2	**53**	163	17	233
test 3	**59**	183	14	256
test 4	**39**	189	16	244
test 5	**49**	182	10	241
AVERAGE	**52**	**176**	**15**	**243**

→

HEA without N5	Violations of:			
	SC 1	SC 2	SC 3	Total
test 1	**172**	130	6	308
test 2	**193**	122	15	330
test 3	**194**	111	20	325
test 4	**193**	106	11	310
test 5	**190**	125	10	325
AVERAGE	**188**	**119**	**12**	**320**

Table 37: Separate Soft Constraint Violations HEA with and without Neighborhood 5

When we split up the objective function value per violation of soft constraint one, two and three we see that with N_5 in the algorithm the violations of SC 1 are significantly less. This is in line with what I expected, as N_5 focuses on clearing out the end-of-day timeslots. The violations of SC 2 are slightly higher, but still the overall effect is clearly positive. The severity of violating SC one, two or three is always equal so adding N_5 to the algorithm unambiguously improves the results. For further reference I will name this neighborhood the 'end-of-day neighborhood'.

Table 39 and 40 give an overview of all used population and local search parameters respectively. To recall the meaning of the population parameters, see figure 12 on p. 44.

Population Size	Diversity Threshold	Mutation Rate Random	Mutation Random Probability	Mutation Rate Smart	Mutation Smart Probability
10	350	10	0,75	2	0,25

Table 38: Final Population Parameters

NLGDA stop criterion	Delta	min	max	Bmin	Bmax	β	Neighborhood Combination
5.000	5E-09	13.000.000	15.000.000	1	3	0	1 - 2 - 3 - 5

Table 39: Final Local Search Parameters

9.2 RESULTS

Table 41 and 42 show the minimum, maximum, and average OFV of ten runs of the algorithm for all twenty instances. The values indicate the SCV's. Every roster in the final results is feasible. The complete table with the values for every run can be found in Appendix. I ran every instance ten times for 636 seconds. An attentive reader might notice the difference in the results for instance one with the results obtained during the parameter testing. When all the parameters were chosen, I deleted all the code that wrote data output files. These files were needed to analyse the effect of the parameters, but for the final algorithm they could be deleted as this speeds up the algorithm considerably. This explains the lower values for instance 1 compared to those obtained during parameter testing.

FINAL RESULTS	Instance									
	1	2	3	4	5	6	7	8	9	10
MINIMUM	213	163	210	359	371	270	239	227	171	213
MAXIMUM	232	191	244	459	452	357	336	266	216	255
AVERAGE	223	182	228	408	411	322	280	252	202	227

Table 40: Final Results Instances 1 - 10

FINAL RESULTS	Instance									
	11	12	13	14	15	16	17	18	19	20
MINIMUM	221	199	266	336	192	206	278	175	329	192
MAXIMUM	240	245	318	431	319	235	397	203	383	264
AVERAGE	234	217	293	366	267	220	333	189	358	228

Table 41: Final Results Instances 11 - 20

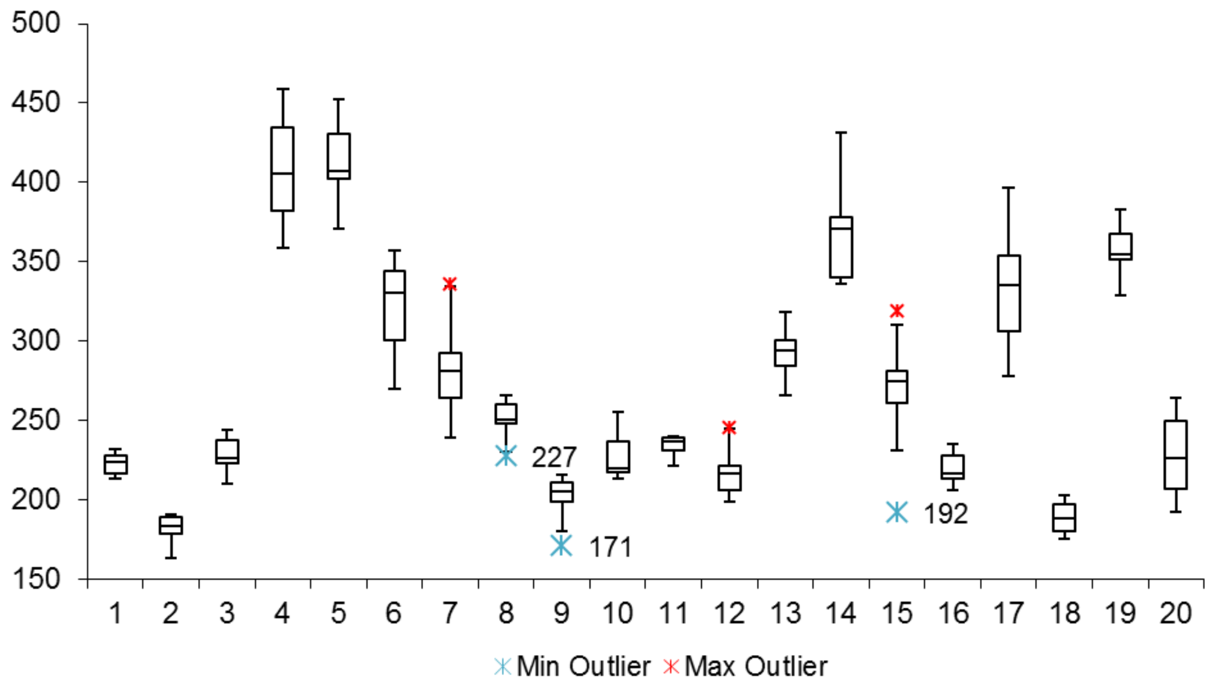
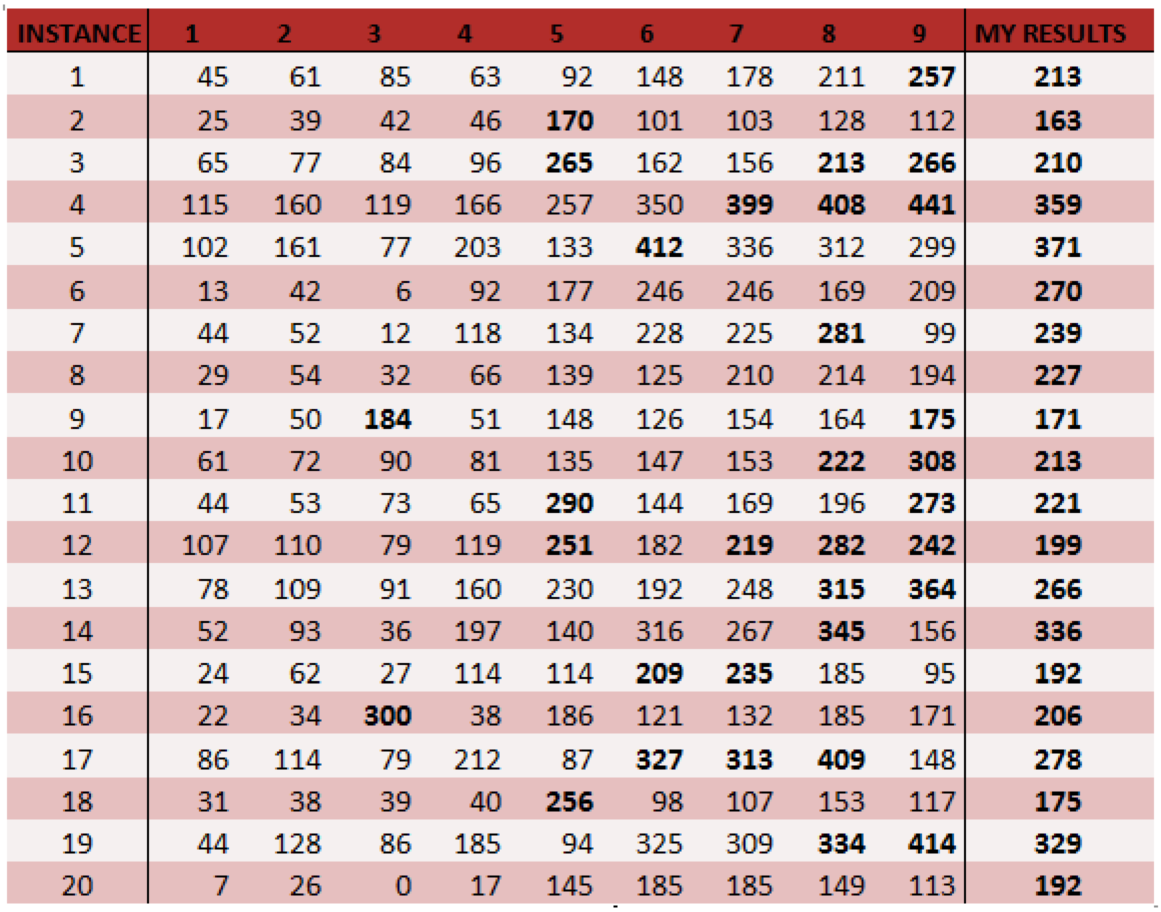


Figure 19: Boxplot of Final Results

Figure 19 shows a boxplot of all the results. The results are quite consistent for most instances and have an interquartile range of less than 50. If the values were not consistent this could be an indication of a bug in the program or an irregularity that caused the algorithm to get stuck during some runs. Luckily this is not the case.

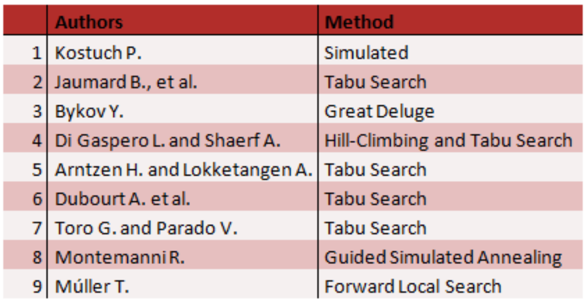
9.3 BENCHMARKING

Standing alone these results do not say much, so I compared them to the official results of the participants of the competition, as can be seen in table 43. This shows that the algorithm produces good results. For most instances it finds objective function values that are better than the results of one of the algorithms ranked third, fifth, sixth, seventh, eighth, or ninth in the competition. The values for which it scores better are indicated in bold. Only for instance six, eight, and twenty my algorithm scores lowest. From this I can confidently conclude that the proposed Hybrid Evolutionary Algorithm is a successful approach to the problem of the International Timetabling Competition of 2003.



INSTANCE	1	2	3	4	5	6	7	8	9	MY RESULTS
1	45	61	85	63	92	148	178	211	**257**	**213**
2	25	39	42	46	**170**	101	103	128	112	**163**
3	65	77	84	96	**265**	162	156	**213**	**266**	**210**
4	115	160	119	166	257	350	**399**	**408**	**441**	**359**
5	102	161	77	203	133	**412**	336	312	299	**371**
6	13	42	6	92	177	246	246	169	209	**270**
7	44	52	12	118	134	228	225	**281**	99	**239**
8	29	54	32	66	139	125	210	214	194	**227**
9	17	50	**184**	51	148	126	154	164	**175**	**171**
10	61	72	90	81	135	147	153	**222**	**308**	**213**
11	44	53	73	65	**290**	144	169	196	**273**	**221**
12	107	110	79	119	**251**	182	**219**	**282**	**242**	**199**
13	78	109	91	160	230	192	248	**315**	**364**	**266**
14	52	93	36	197	140	316	267	**345**	156	**336**
15	24	62	27	114	114	**209**	**235**	185	95	**192**
16	22	34	**300**	38	186	121	132	185	171	**206**
17	86	114	79	212	87	**327**	**313**	**409**	148	**278**
18	31	38	39	40	**256**	98	107	153	117	**175**
19	44	128	86	185	94	325	309	**334**	**414**	**329**
20	7	26	0	17	145	185	185	149	113	**192**

Table 42: Comparison Of Results with Official Competition Results



	Authors	Method
1	Kostuch P.	Simulated
2	Jaumard B., et al.	Tabu Search
3	Bykov Y.	Great Deluge
4	Di Gaspero L. and Shaerf A.	Hill-Climbing and Tabu Search
5	Arntzen H. and Lokketangen A.	Tabu Search
6	Dubourt A. et al.	Tabu Search
7	Toro G. and Parado V.	Tabu Search
8	Montemanni R.	Guided Simulated Annealing
9	Múller T.	Forward Local Search

10. CONCLUSION

In this thesis I studied the university course timetabling problem on the basis of the International Timetabling Competition of 2003. The university course timetabling problem is a combinatorial optimization problem where courses have to be assigned to a suitable room and planned into a weekly schedule of timeslots. A timetable strongly affects the life of students, teachers and other university staff members as well as the quality of education at the university. It is therefore essential for every institution to provide prime timetables that take into account the requirements for every course, the educational policy of the university, and the preferences of students and teachers.

For several decades research has been done towards finding methods that are able to construct good timetables. In 2003 the EURO Working group on Automated Timetabling (WATT) organized, together with the Metaheuristics Network, an International Timetabling Competition (ITC 2003). The aim was to create better understanding between researchers and practitioners by allowing emerging techniques to be trialed and tested on real-world models of timetabling problems. Also, the organizers hoped that conclusions of the competition would stimulate debate and research in the field of timetabling. The subject problem of this competition has since been widely accepted as a benchmark problem in the timetabling community. It is this problem that I extensively studied in this thesis, and for which I have developed a method to solve it.

The university course timetabling problem is a problem with such a high complexity that it has to be tackled with heuristic and metaheuristic approaches. Many solution methods have been proposed in the literature but the ideal technique to find optimal timetables has not yet emerged. I hope that my research can contribute to the on-going optimization of methods to solve the timetabling problem.

The algorithm I propose is a combination of an evolutionary algorithm with a non-linear great deluge algorithm, it is thus a hybrid metaheuristic method. I tested the algorithm on the datasets of the International Timetabling Competition of 2003. The results obtained can compete with the results obtained by the algorithms that ended seventh, eighth, and ninth in the competition, and thus prove that it is a good performing algorithm.

For future research I suggest to experiment with the end-of-day neighborhood proposed in this thesis. It has not yet been extensively studied in literature, and comparison of the performance of the algorithm with and without this neighborhood shows promising results.

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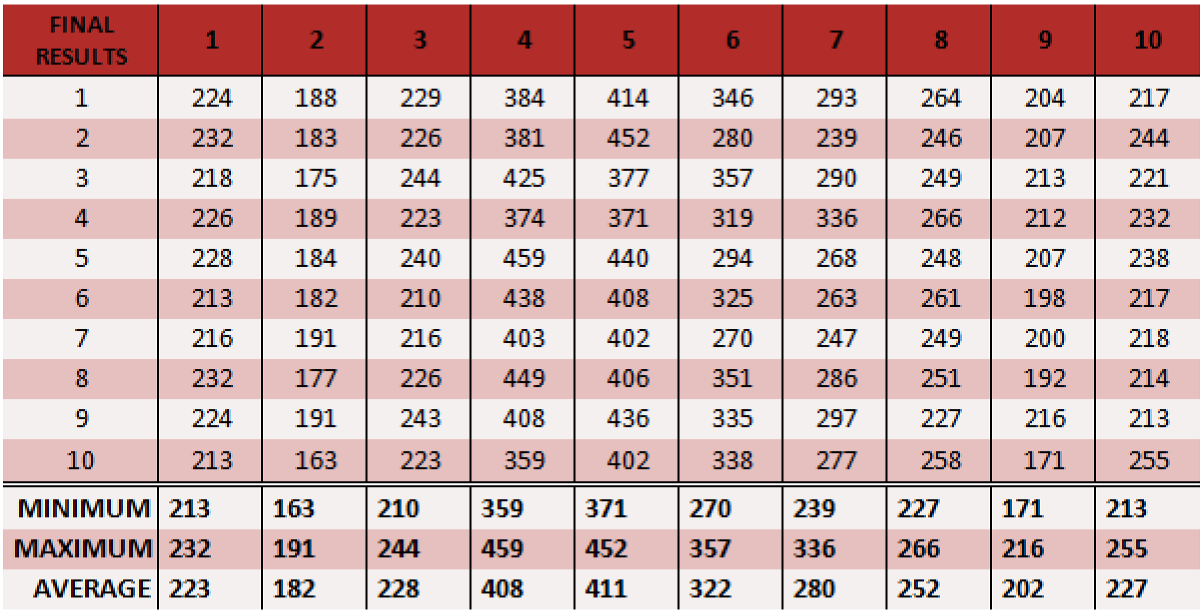
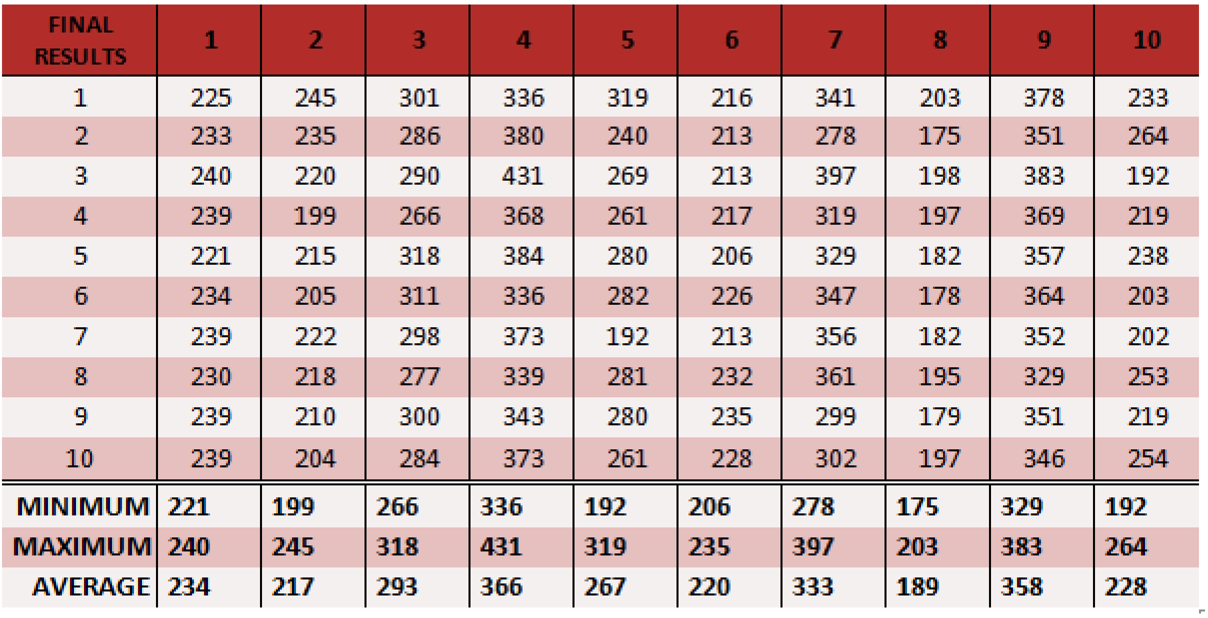
APPENDIX

COMPLETE OVERVIEW OF FINAL OBTAINED RESULTS



FINAL RESULTS	1	2	3	4	5	6	7	8	9	10
1	224	188	229	384	414	346	293	264	204	217
2	232	183	226	381	452	280	239	246	207	244
3	218	175	244	425	377	357	290	249	213	221
4	226	189	223	374	371	319	336	266	212	232
5	228	184	240	459	440	294	268	248	207	238
6	213	182	210	438	408	325	263	261	198	217
7	216	191	216	403	402	270	247	249	200	218
8	232	177	226	449	406	351	286	251	192	214
9	224	191	243	408	436	335	297	227	216	213
10	213	163	223	359	402	338	277	258	171	255
MINIMUM	**213**	**163**	**210**	**359**	**371**	**270**	**239**	**227**	**171**	**213**
MAXIMUM	**232**	**191**	**244**	**459**	**452**	**357**	**336**	**266**	**216**	**255**
AVERAGE	**223**	**182**	**228**	**408**	**411**	**322**	**280**	**252**	**202**	**227**



FINAL RESULTS	1	2	3	4	5	6	7	8	9	10
1	225	245	301	336	319	216	341	203	378	233
2	233	235	286	380	240	213	278	175	351	264
3	240	220	290	431	269	213	397	198	383	192
4	239	199	266	368	261	217	319	197	369	219
5	221	215	318	384	280	206	329	182	357	238
6	234	205	311	336	282	226	347	178	364	203
7	239	222	298	373	192	213	356	182	352	202
8	230	218	277	339	281	232	361	195	329	253
9	239	210	300	343	280	235	299	179	351	219
10	239	204	284	373	261	228	302	197	346	254
MINIMUM	**221**	**199**	**266**	**336**	**192**	**206**	**278**	**175**	**329**	**192**
MAXIMUM	**240**	**245**	**318**	**431**	**319**	**235**	**397**	**203**	**383**	**264**
AVERAGE	**234**	**217**	**293**	**366**	**267**	**220**	**333**	**189**	**358**	**228**