TIMETABLE SCHEDULING USING RULE-BASED TECHNIQUE

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ABSTRACT

Timetabling is a problem of allocating a timeslot for all lectures, lab and tutorials in the problem instances within a limited number of permitted timeslots, in such a way that none of the specified hard constraints are violated. In addition to the hard constraints, there are often many soft constraints which are desirable to satisfy. In this study, the timetable scheduling for Faculty of Computer System & Software Engineering (FSKKP) of University College of Engineering & Technology Malaysia (KUKTEM) has been studied to develop new prototype software for generating timetable. Basically, FSKKP is still using human power in generating its timetable instead of using timetable scheduling software. Since the timetable is configured manually, it is time-consumed as well as it needs extra human resources to manage it. The university has its own system for generating timetable which involving all of the faculties, but it is still in maintenance for perfecting and enhancement since it still has weaknesses. In this project development, the prototype will be implemented with rule-based approach as the solution to overcome the timetable constraints and rules. The success of implementation and development of this project is expected to help in reducing the time consumed and human power in generating timetable for FSKKP. Indeed, it is also expected to generate a well-developed timetable which giving the best solution in overcome the timetabling constraints and rules of FSKKP.

ABSTRAK

Penjadualan merupakan satu masalah untuk menyusun semua aktiviti pembelajaran seperti kuliah, bengkel dan tutorial mengikut masa dan tempat seterusnya kemudian dimuat dan disusunkan dalam bentuk jadual tanpa melanggar atau mengindarkan kengkangan utama seperti kekangan universiti dan fakulti. Dalam kajian ini, penyusunan jadual waktu bagi Fakulti Sistem Komputer & Kejuruteraan Perisian (FSKKP) di Kolej Universiti Kejuruteraan & Teknologi Malaysia (KUKTEM) telah dikaji untuk tujuan pembangunan model perisian yang mampu menyusun jadual pembelajaran dengan berkesan. Penyusunan jadual pembelajaran di FSKKP masih lagi dijalankan secara manual di mana ianya memakan masa yang lama dan menggunakan banyak tenaga manusia. Organisasi KUKTEM telah pun mempunyai sistem untuk menyusun jadual pembelajaran yang melibatkan semua fakulti di universiti tersebut. Namun demikian, sistem tersebut masih lagi dalam proses pembaikan disebabkan masih lagi mempunyai kelemahan. Dalam projek ini, model yang dibangunkan menggunakan teknik pangkalan peraturan dalam melaksanakan aktiviti penjadualan. Daripada projek ini, diharap ia dapat mengurangkan masa dan tenaga manusia untuk pembangunan jadual pembelajaran di FSKKP yang merupakan masalah utama yang perlu diatasi. Dengan pembangunan projek ini juga, diharap ia dapat membina jadual yang berkesan dengan menitik beratkan kengkangan-kengkangan yang perlu diambil kira.

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LIST OF ABBREVIATIONS

etc.	-	etcetera
e.g.	-	for example [exempli gratia]
i.e.	-	that is [id est]
AI	-	Artificial Intelligence
BCS	-	Bachelor Computer Science
CHI	-	Set of children
CPU	-	Computer Processing Unit
DCS	-	Diploma Computer Science
FSKKP	-	Fakulti Sistem Komputer & Kejuruteraan Perisian
GA	-	Genetic Algorithm
GEN	-	Number of generation
JAD	-	Joint Application Development
KUKTEM	-	Kolej Universiti Kejuruteraan & Teknologi Malaysia
LFT	-	Latest finish time
LST	-	Latest start time
POP	-	Population
PPSS	-	Pusat Pembangunan Sains Sosial
RAD	-	Rapid Application Development
RAM	-	Random Access Memory
RCPSP	-	Representation and self-adaptation
RS	-	Resource strength
SDLC	-	Software Development Life Cycle
SGS	-	Schedule generation scheme

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CHAPTER 1

INTRODUCTION

1.1 Introduction

The management of timetabling in the educational institution is very crucial as to have a well-managed schedule lectures, labs and tutorials. This is important in distributing the resources needed in a proper way without any faults. As seen nowadays, a lot of solution or application that helps in generating a timetable which has been developed in an artificial intelligent way. Some of the artificial intelligent methods that available are expert system, genetic algorithm, fuzzy logic and etc. Each method has their own way of performing their solution.

The TimeTabler is a software that will assists the Faculty of Computer and Software Engineering (FSKKP) to schedule a timetable in the faculty. It automatically will schedule the time and subject for a lecture, lab or tutorial class for specific time and place. Indeed, this software will be implemented with the required rules and constraints that need to be complied. Through TimeTabler, schedule for specific lecturer or course can be view as a report. Basically, this software will help in develop a well-distributed timetable and overcome the constraints in an intelligent way.

1.2 Problem Statement

1.2.1 Current System

The current system for timetabling in the faculty manages to develop a timetable. Based on the previous timetable, it is found that the system does not really helps in scheduling timetable wisely. Therefore, there is still human power needed to configure the timetable manually. Below are some of the problems faced by the current system:

(a) Classroom clashing between for two courses at the same time
(b) Classroom provided cannot support the number of student
(c) Timetable for courses in FSKKP takes approximately three days to be manually-developed.
(d) Still in need for human power for timetable configuration.

1.2.2 Current System Process

For every algorithm, it is crucial to understand the flow of process on how it is executed. This will determine the success of the algorithm implementation through coding and logic programming. The process flow for KUKTEM timetabling algorithm can be referred in Appendix A.

1.3 Objectives

For every project development, it must have its aims so the project's success can be measured into some extent. Therefore, below are the objectives of this project:

(a) TimeTabler is a prototype software for developing a well-distributed timetable for every course in FSKKP.

(b) Provide a full report of timetable for every course in FSKKP

(c) Reduce the time consumed as well as the human power in arranging a schedule and overcome the conventional way of managing a schedule

1.4 Scopes

Basically, this software is mainly developed for the FSKKP to manage and establish a well-organized schedule. The courses that involved are Bachelor of Software Engineering (BCS) and Diploma of Software Engineering (DCS) for each batch. In this scheduling, it only involves with the subjects in the FSKKP and the subjects from Pusat Pembangunan Sains Sosial (PPSS) for university subjects.

This project is going to be developed for Windows platform and it uses the data or resources and subjects for semester 2 year 2004/2005. It will use the visual basic programming as code generation and Microsoft Access as the database management.

The TimeTabler is well-designed rule-based application to comply the following constraints that critically required to be emphasized:

(a) There will be no class or lecture that is clashing.

(b) The room for each class, tutorial or lab must be able to support the number of student.

(c) Must satisfy the university constraints such as there should be no class at 8.am on every Monday, no subject is scheduled in the evening for every Wednesday, and schedule should not have class at 1.00 pm and for faculty meeting; on Tuesday 8 am to 10 am.

(d) The TimeTabler should be able to give a final report of timetable for every course in the FSKKP.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Timetabling is a great importance for educational institutions and has to be solved numerous times at each institution consuming expensive human and computer resources. Timetabling can be defined as the problem of assigning a set of schedule into a given set of classrooms over a limited number of time periods in such a way that there are no conflicts between any two classes. That is no student should be required to attend two classes at the same time and no two classes should be assigned to the same classroom during overlapping time periods. At the same time, it is also need to consider the capacity of the room, lecturers that involved, time and some other constraints.

There are a lot of applications that has been developed and available in the market. These applications aim is to generate a well-distributed timetable in respective way of solution depending its method or artificial intelligent algorithm. A lot of algorithms or methods available nowadays and widely used in the area of timetabling, such as genetic algorithm, fuzzy logic, expert system and etc.

2.2 Methodology in Timetabling

2.2.1 Rule-Based Approach

2.2.1.1 Introduction to Rule-Based System

Rule-based system use a set of assertions, which collectively form the 'working memory', and a set of rules that specify how to act on the assertion set, a rule-based system can be created. Rule-based systems are fairly simplistic, consisting of little more than a set of if-then statements, but provide the basis for so-called "expert systems" which are widely used in many fields. The concept of an expert system is where the knowledge of an expert is encoded into the rule set. When exposed to the same data, the expert system will perform in a similar manner to the expert.

Rule-based systems are a relatively simple model that can be adapted to any number of problems. As with any system, a rule-based system has its strengths as well as limitations that must be considered before deciding if it's the right technique to use for a given problem. Overall, rule-based systems are really only feasible for problems for which any and all knowledge in the problem area can be written in the form of if-then rules and for which this problem area is not large. If there are too many rules, the system can become difficult to maintain and can suffer a performance hit. Basically, to create a rule-based system for a given problem, the following must have (or created) [15]:

a) A set of facts to represent the initial working memory. This should be anything relevant to the beginning state of the system.

b) A set of rules. This should encompass any and all actions that should be taken within the scope of a problem, but nothing irrelevant. The number of rules in the system can affect its performance, so you don't want any that aren't needed.

c) A condition that determines that a solution has been found or that none exists. This is necessary to terminate some rule-based systems that find themselves in infinite loops otherwise.

2.2.1.2 Theory of Rule-Based Systems

The rule-based system itself uses a simple technique whereby it starts with a rule-base, which contains all of the appropriate knowledge encoded into If-Then rules, and a working memory, which may or may not initially contain any data, assertions or initially known information. The system examines all the rule conditions (IF) and determines a subset, the conflict set, of the rules whose conditions are satisfied based on the working memory. Of this conflict set, one of those rules is triggered (fired).

Which one is chosen is based on a conflict resolution strategy. When the rule is fired, any actions specified in its THEN clause are carried out. These actions can modify the working memory, the rule-base itself, or do just about anything else the system programmer decides to include. This loop of firing rules and performing actions continues until one of two conditions is met: there are no more rules whose conditions are satisfied or a rule is fired whose action specifies the program should terminate.

Which rule is chosen to fire is a function of the conflict resolution strategy. Which strategy is chosen can be determined by the problem or it may be a matter of preference. In any case, it is vital as it controls which of the applicable rules are fired and thus how the entire system behaves. There are several different strategies, but here are a few of the most common [15].

First Applicable: If the rules are in a specified order, firing the first applicable one allows control over the order in which rules fire. This is the simplest strategy and has a potential for a large problem: that of an infinite loop on the same rule. If the working memory remains the same, as does the rule-base, then the conditions of the first rule have not changed and it will fire again and again. To solve this, it is a common practice to suspend a fired rule and prevent it from re-firing until the data in working memory, that satisfied the rule's conditions, has changed.

Random: Though it doesn't provide the predictability or control of the first-applicable strategy, it does have its advantages. For one thing, its unpredictability is an advantage in some circumstances (such as games for example). A random strategy simply chooses a single random rule to fire from the conflict set. Another possibility for a random strategy is a fuzzy rule-based system in which each of the rules has a probability such that some rules are more likely to fire than others.

Most Specific: This strategy is based on the number of conditions of the rules. From the conflict set, the rule with the most conditions is chosen. This is based on the assumption that if it has the most conditions then it has the most relevance to the existing data.

Least Recently Used: Each of the rules is accompanied by a time or step stamp, which marks the last time it was used. This maximizes the number of individual rules that are fired at least once. If all rules are needed for the solution of a given problem, this is a perfect strategy.

"Best" rule: For this to work, each rule is given a 'weight,' which specifies how much it should be considered over the alternatives. The rule with the most preferable outcomes is chosen based on this weight.

2.2.1.3 Forward-Chaining in Rule-Based Systems

Rule-based systems, as defined above, are adaptable to a variety of problems. In some problems, information is provided with the rules and the AI follows them to see where they lead. An example of this is a medical diagnosis in which the problem is to diagnose the underlying disease based on a set of symptoms (the working memory). A problem of this nature is solved using a forward-chaining, data-driven, system that compares data in the working memory against the conditions (IF parts) of the rules and determines which rules to fire.

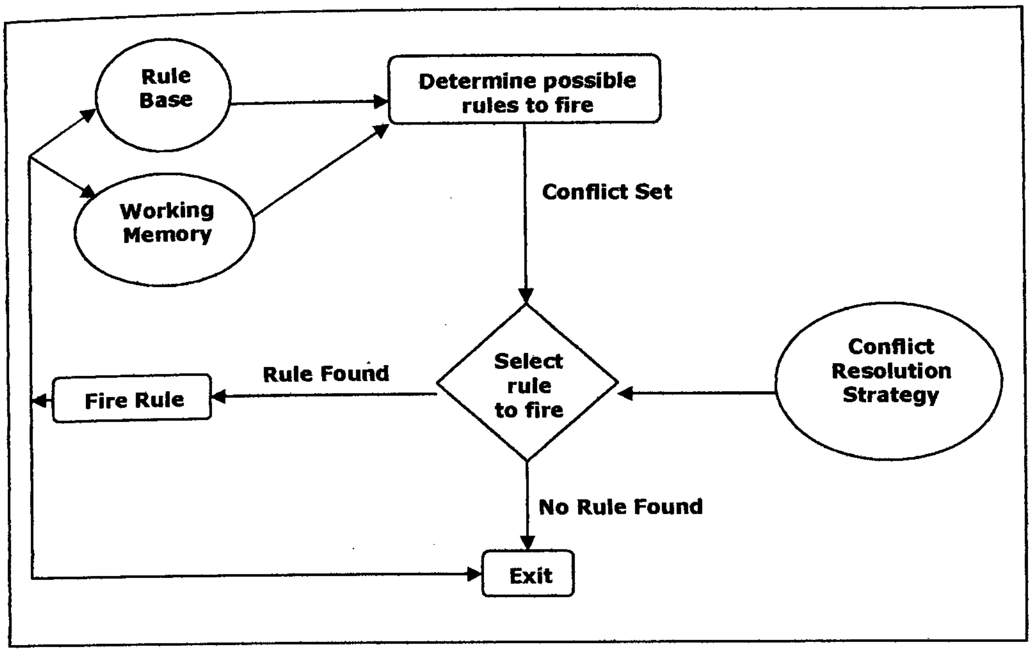

Figure 2.1: Forward-Chaining in Rule-based System [15]

2.2.2 Fuzzy Logic Approach

Fuzzy scheduling provides the possibility to deal with the inherent dynamic and incompleteness of the scheduling area. It allows the representation (by fuzzy sets and linguistic variables) and the inference (by fuzzy rules) from vaguely formulated knowledge. The main types of imprecise scheduling information addressed by fuzzy sets are:

(a) Vaguely defined dates or durations, e.g., due dates,

(b) Vague definitions of preferences, e.g., preferences between alternatives,

(c) Uncertainty about the value of scheduling parameters, e.g., process times,

(d) Aggregated knowledge, e.g., machine groups instead of individual machines.

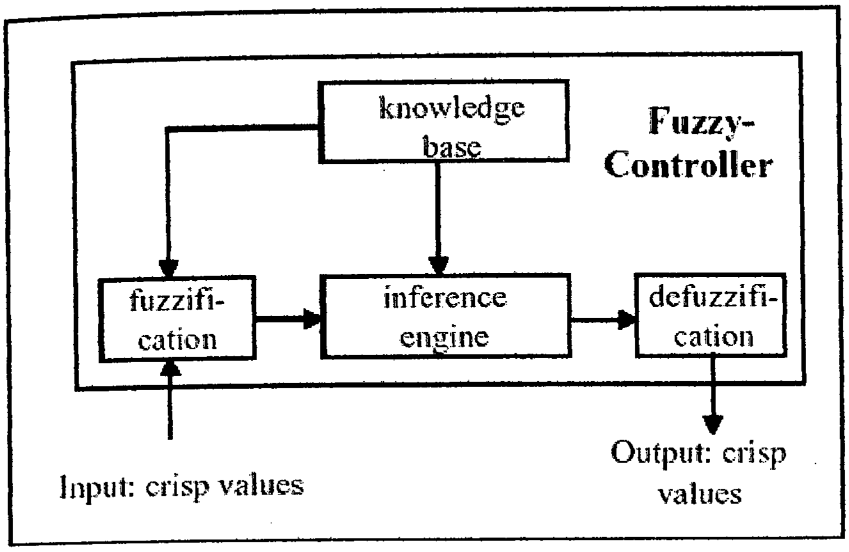

Figure 2.2 : Fuzzy controller [16]

To handle the imprecise information with fuzzy controllers (Figure 2.2), the following steps have to be performed:

(a) Transformation of scheduling data into a knowledge representation that can be handled by a fuzzy controller (fuzzification). Imprecise knowledge is represented by linguistic variables denoting the possible values, e.g., capacity of machine groups by {very low, low, normal, high, very high}. For each of the possible values a membership function (e.g., triangular) is given, which is used in combining and processing the fuzzy sets.

(b) Processing of the fuzzy scheduling knowledge towards a decision by means of given rules and integration of fuzzy arithmetic to deal with imprecise or vague data. Fuzzy sets and rules are stored in the knowledge base of the fuzzy controller.

(c) Transformation of the fuzzy scheduling decision into crisp scheduling data (defuzzification), e.g., to determine concrete dates for operations. The principal advantage of fuzzy scheduling is the possibility to focus on the significant scheduling decisions; a main disadvantage is the computational effort necessary. First approaches have been reported in the late 1980s [13; 14] and research is ongoing [11; 12].

```
k := number of unscheduled exams;
For u := 1 to k
   Select exam[u];
   Find timeslots where exam[u] can be inserted with minimum number
   of scheduled exams need to be removed from the timeslot;
   If found more than one slot with the same number of scheduled ex-
   ams need to be removed
     Select a timeslot randomly from the candidate list of slots, ts;
   End if
   c :=  number of exam in timeslot ts_u that conflict with exam[u];
   For m := 1 to c
       Select exam[m];
      If found another timeslot with minimum cost to move exam[m]
        Move exam[m] to the timeslot;
      else
        Bump back exam[m] to unscheduled exam list;
      End if
   End for
   Insert exam[u] to timeslot ts_u;
   Remove exam[u] from unscheduled exam list;
End for
```

Figure 2.3 : Example of algorithm for Fuzzy logic [5]

2.2.3 Genetic Algorithm Approach

2.2.3.1 Basic Scheme

Genetic algorithms in Holland [9] and Goldberg [10] apply the principles of biological evolution to solve optimization problems. They combine existing solutions in order to form new ones. Together with a survival-of-the-fittest strategy, this leads to successively better solutions for the problem to be solved. The GA framework starts with the computation of an initial population which describes in Subsection 2.2.3.3, i.e., the first generation. The number of individuals in the population is referred to as *POP* which is assumed to be an even integer.

The GA then determines the fitness values of the individuals of the initial population. After that, the population is randomly partitioned into pairs of individuals.

To each resulting pair of (parent) individuals, it applies the crossover operator (see Subsection 2.2.3.4) to produce two new (child) individuals. Subsequently, apply the mutation operator (see Subsection 2.2.3.5) to the genotypes of the newly produced children. After computing the fitness of each child individual, add the children to the current population, leading to a population size of 2 $\cdot$*POP*. Then apply the selection operator (see Subsection 2.2.3.6) to reduce the population to its former size *POP*. Doing so, will obtain the next generation to which, again apply the crossover operator and so on.

This process is repeated for a pre-specified number of generations which is denoted as *GEN* or, alternatively, until a given CPU time limit is reached. More formally, the GA scheme can be summarized as follows. POP denotes the current population (i.e., a set of individuals), and CH I is the set of children. *G* is the current generation number. Note that exactly *POP* $\cdot$ *GEN* individuals (and thus schedules) are computed if a time limit is not given.

$G := 1$;
generate initial population $\mathcal{POP}$;
compute fitness for individuals $I \in \mathcal{POP}$;
WHILE $G < GEN$ **AND** time limit is not reached **DO**
BEGIN
    $G := G + 1$;
    produce children $\mathcal{CHI}$ from $\mathcal{POP}$ by crossover;
    apply mutation to children $I \in \mathcal{CHI}$;
    compute fitness for children $I \in \mathcal{CHI}$;
    $\mathcal{POP} := \mathcal{POP} \cup \mathcal{CHI}$;
    reduce population $\mathcal{POP}$ by means of selection;
END.

Figure 2.4 : Genetic Algorithm [4]

2.2.3.2 Representation and Self-Adaptation

For many optimization problems, GA does not operate directly on the solutions for the problems. Instead, they make use of problem-specific representations of the solutions. The genetic operators modify the representation which is then transformed into a solution by means of a so-called decoding procedure.

For the RCPSP, a solution is given by a schedule $S = (s1, \ldots, sJ)$ which assigns a start time $s\,j$ to every activity j. As outlined in Hartmann [11], such a solution can be represented within a GA by an activity list $l = (j1, \ldots, jJ)$. An activity list must be precedence feasible, that is, any activity must occur in the list after all its predecessors. Formally, that is Pji _ $\{0, j1, \ldots, ji\text{-}1\}$ for i=1, . . . ,J. The activity list is transformed into a schedule by a decoding procedure which is called serial schedule generation scheme (SGS). The serial SGS constructs schedules from activity lists as follows: First, the dummy source activity is started at time 0. Then the activities are scheduled in the order that is prescribed by the list $(j1, \ldots, jJ)$.

Thereby, each activity is assigned the earliest precedence and resource feasible start time. In fact, in Hartmann [11] it is shown that the activity list representation (together with the serial SGS as decoding procedure) leads to better results than other representations for the RCPSP. In the context of priority rule based heuristics, another scheduling algorithm for the RCPSP, the so-called parallel SGS, has been employed [20]. It works as follows: Having scheduled the dummy sink activity at time 0, the parallel SGS computes a so-called decision point which is the time at which an activity to be scheduled is started.

This decision point is determined by earliest finish time of the activities currently in process. For each decision point, the set of eligible activities is computed as the set of those activities that can be feasibly started at the decision point. The eligible activities are selected successively and started until none are left. Then the next decision point and a related set of eligible activities are computed. This is repeated until all activities are feasibly scheduled.

To the best of knowledge, all metaheuristics in the RCPSP literature that employ the activity list representation also make use of the serial SGS as decoding procedure as agreed in Baar et al. [21], Boctor [22], Bouleimen and Lecocq [23], Hartmann [24], and

Pinson et al. [25]. Usually, no reason for the selection of the serial SGS is given—the serial SGS appears to be the "natural choice."

Thus, here it is proposed to use not only the serial but also the parallel SGS as decoding procedure for the activity list representation. In fact, the parallel SGS can easily be applied to activity lists: In each step, simply choose that activity from the eligible set that has the lowest index in the activity list.

Now there are two possible decoding procedures for the activity list representation of the RCPSP. This leads to the question which of them should be used. In fact, there is no general answer to this question. This is due to the differences between the serial and the parallel SGS: Whereas the serial SGS constructs so-called active schedules, the parallel one constructs so-called non-delay schedules [27].

The set of the non-delay schedules is a (in most cases proper) subset of the set of the active schedules. While the set of the active schedules always contains an optimal schedule, this does not hold for the set of the non-delay schedules. Consequently, the parallel SGS may miss an optimal schedule. On the other hand, it produces schedules of good average quality because it tends to utilize the resources as early as possible, leading to compact schedules.

These result in different behaviors of the SGS in computational experiments based on Kolisch [20] and Hartmann and Kolisch [26]. On instances with many activities and/or scarce resource capacities, the parallel SGS performs better than the serial one. Moreover, if long computation times are allowed (i.e., if many schedules can be computed), the serial SGS leads to better results than the parallel one.

These observations can be explained as follows: Many activities and scarce resources imply larger search spaces, where the focus on compact, but often only suboptimal non-delay schedules is a promising heuristic strategy. Longer computation times may allow finding an optimal or a near optimal solution, which is typically only possible if the serial SGS is used.

However, it is usually impossible to predict which of the SGS will perform better for an arbitrary instance of the RCPSP. The idea is now to allow both SGS to be employed as decoding procedures within the GA. To do so, define the genotype as follows: An individual $I = (l, SGS)$ consists of an activity list l and an indicator

$$SGS = \begin{cases} 1, & \text{if activity list l is to be decoded by the serial SGS} \\ 0, & \text{if activity list l is to be decoded by the parallel SGS.} \end{cases}$$

For a given individual, compute a schedule using the SGS specified in the genotype. The fitness of the individual is defined as the make span of the schedule. That is, a lower fitness implies a better individual and thus a higher chance to survive.

The extended representation proposed here includes an additional gene that determines the SGS type to be used as decoding procedure for the related activity list. As with all genes in GAs, also this one is subject to the genetic operators' crossover, mutation, and selection. Therefore, the SGS type leading to better results will survive while the other one will probably die over the generations. Thus the mechanism of evolution decides for the specific instance currently to be solved which decoding procedure is the more promising one. This enables the GA to adapt itself dynamically to each instance, leading to what it is call a self-adapting GA.

2.2.3.3 Initial Population

In initial population, it is crucial to define how to determine an initial population containing *POP* individuals of the genotype introduced above. Basically, it will proceed in two steps. First, consider the construction of an activity list. Second, describe the selection of the decoding procedure to be used, i.e., one of the two SGS. An activity list is constructed by a modified priority rule based sampling heuristic [20]. The next activity for the list is successively chosen from those unscheduled activities the predecessors of which have already been selected for the list. This way, it will obtain a precedence feasible activity list. The decision which activity is chosen next is made on the basis of one of two well-known priority rules. Firstly, select the priority rule; either the LFT (latest finish time) or the LST (latest start time) rule is chosen with a probability of 0.5 each.

From the resulting priority values of the activities, derive regret based biased selection probabilities that are used to select the next activity (for details on the priority rules and the regret based biased sampling approach, refer to Kolisch [20]). Using two good priority rules and a randomized activity selection method leads to a diversified initial population of good activity lists. Next, choose an SGS in order to make the current activity list a complete genotype. Of course, both SGS must appear in the population because the genetic algorithm needs to decide which of them is more promising. Then, examined the following three alternative approaches:

a) The most straightforward method is to select each of the SGS types with a probability of $p = 0.5$.

b) The following idea was designed to lead to a good initial distribution of the SGS types with respect to the project actually to be scheduled. It is discussed above that, roughly explained, the serial SGS is more favorable for smaller projects. This motivated the following approach where the probability to select the serial SGS is defined as p serial = a J, where a is a constant. Clearly, set p parallel = 1- p serial. This way, the more activities it will have in a project, the higher the probability to select the parallel SGS in the initial population.

c) Similarly, the parallel SGS is superior in case of scarce resource capacities. A formal measure for the scarceness is the resource strength *RS* [28]. Low resource strength implies scarce capacities. Thus, simply set p serial = *RS*. Again, set p parallel =1- p serial. Obviously, low resource strength leads to a low probability for selecting the serial SGS (note that RS is between 0 and 1 by definition).

In computational experiments with a large number of test instances, these three approaches gave similar results on the average. This indicates that the initial distribution is not crucial for the evolution as long as both SGS obtain a sufficient fraction in the initial population. As none of the methods was clearly superior, select the simplest approach (a).

2.2.3.4 Crossover

Let's assume that two individuals of the current population have been selected for crossover. Thus, there will be mother individual M =(lM,$SGSM$) and a father individual F =(lF,$SGSF$). Now two child individuals have to be constructed, a daughter D = (lD,$SGSD$) and a son S = (lS,$SGSS$).

First, start with a definition of the daughter D. In a first step, determine the daughter's activity list lD. Combining the parent's activity lists, make sure that each activity appears exactly once in the daughter's activity list. Therefore, adapt a general crossover technique presented by Reeves [31] for permutation based genotypes. This approach also secures that precedence feasibility is maintained. Perform a two-point crossover for which will draw two random integers $q1$ and $q2$ with 1 _ $q1 < q2$ _ J. Now the daughter's activity list lD is determined by taking the activity list of the positions i = 1, . . . ,$q1$ from the mother, that is,

$$j_i^D := j_i^M$$

The positions i=$q1$+1, . . . ,$q2$ are derived from the father. However, the activities already selected may not be considered again. Then, this will be obtained:

$$j_i^D := j_k^F \quad \textit{where k is the lowest index such that} \quad j_k^F \notin \left\{ j_1^D, \ldots, j_{i-1}^D \right\}$$

The remaining positions i = $q2$+1, . . . ,J are again taken from the mother, that is,