Genetic algorithm for process optimization in hospitals

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ABSTRACT

In 2004 new reimbursement policies for hospitals based on Diagnosis Related Groups (DRGs) were introduced in Germany. These force hospitals to minimize the cost of treatment and improve quality of care, in order to attract more patients and become more competitive. To achieve these goals hospital processes need to be optimized and compared with processes in competing hospitals. Regarding this, the scheduling of patient treatment poses a huge challenge. For purpose of analysis, optimization and validation of hospital processes - especially interaction of processes and effects of interconnection - it is necessary to develop validated and executable models. In (Salzwedel et. al. 2007) the processes of a cancer treatment center were modeled and optimized. This paper describes our developments toward automatically optimizing scheduling of patients, reducing processing time and optimizing resource usage in a cancer center using genetic algorithms.

1. INTRODUCTION

Health care costs in Germany have been rising continuously. They increased by 34.2% to 278.3 billion Euros within 1999 and 2009 and became the highest in Europe (Statistisches Bundesamt 2012). To overcome this problem, in 2004 a new reimbursement system for hospital services based on disease patterns was enacted by the German government. Following these new reimbursement rules, hospitals are no longer reimbursed according to the number of days a patient is cared for, based on Diagnosis Related Groups (DRGs), independent of the actual treatment time. Now hospitals have to reduce processing time and resources for patient treatment, in order to reduce costs. In this context the income of hospitals can be defined as:

Income = (DRG-payment – treatment costs) x number of Patients treated.

If treatment costs are reduced and the number of patients treated is increased, income and profit of hospitals grow. Treatment costs are strongly related to processing time and the number of hospital resources used for treatment. Processing time for patients can be defined as:

Processing time (hospital residence time) = treatment time + waiting time.

Measurement of processing time is a common instrument. By optimizing and reducing processing time, hospital resources can be used to treat more patients and so increase income. The mean hospital residence time in Germany is 20% higher than in comparable European countries (Statistisches Bundesamt 2011). Hence, there is a potential for optimizing processing time to reduce treatment costs.

Kühn showed that scheduling of patient treatment has a large influence on reducing processing time and increasing efficient usage of hospital resources (Kühn 2006). Rixen and Hackl demonstrated that genetic algorithms can optimize complex scheduling problems of production processes (Rixen 1997; Hackl 2000).

This paper describes the application of a genetic algorithm for optimizing patient scheduling processes in hospitals for an example of a cancer treatment center utilizing computer simulation. For modeling, simulation, validation and optimization the SW tool MLDesigner is used (Mission Level Design Inc. 2011). Section 2 points out the benefits of using genetic algorithms instead of other heuristics or other mathematic methods. Section 3 represents the current developments in scheduling patients in hospitals. Section 4 describes the development and structure of the genetic algorithm utilized. Furthermore, this section shows how the algorithm is linked to the model of the cancer treatment center. Section 5 summarizes the results.

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2. GENETIC ALGORITHM

A genetic algorithm is a modern search algorithm for optimization based on the mechanisms of natural evolution. It avoids getting stuck at a local maximum of a search space and can move very flexibly in it. Genetic algorithms belong to the group of meta heuristics. Heuristics are search methods for approximate solutions. Meta heuristics are generic principles and schemata for diverse, basically unspecified problems. They can optimize complex, non-calculable or non-mathematically describable problems and there aren't any restrictions regarding their target function (Nissen 1997, p.248). Genetic algorithms use nature approved methods – evolution – the creation of individuals that perfectly match their environment. Especially reproduction, mutation, recombination and selection in combination are the natural optimizers (Nissen 1997, p.34 ff.; p.164 ff.).

3. CURRENT STAGE OF DEVELOPEMENT

The use of genetic algorithms for scheduling problems in different practical industrial cases is shown by Rixen (Rixen 1997) and Hackl (Hackl 2000). Furthermore, Werber demonstrates the use of genetic algorithm for optimizing visual data of medical applications in hospitals (Werber 2010).

Concerning the scheduling of patients in hospitals a cooperation of the Fraunhofer Institute and a hospital formed a workgroup for Supply Chain Services (SCS) and made advances in modeling and planning patient flow (Kriegel et. al. 2009). Starting point was the assumption that a patient can be located in a hospital during the entire processing time. Based on this, an algorithm was developed that is able to optimize the status in real time. As a result of this optimization, patients get information on where to go next in the clinic process chain. The developed algorithm is based on software agents, which represent supplier and customer of a service. Market mechanisms were implemented and used to reach an optimum. Expense factors and processing time are set up as target functions (Niemann 2006). The algorithm has been tested against a simulation with real data but not implemented in a real system. A forecast and planning of patient flow up front has also not been carried out. The focus was on optimization of the dynamic and continuously changing system status.

Moreover, an experiment in the use of genetic algorithms for scheduling patients in hospitals was carried out for scheduling surgery. This project was set up with HELIOS Kliniken GmbH to test the usage of genetic algorithm and particle swarm optimization in a clinical environment. Surgery planning was defined as a highly dynamic multi criteria optimization problem. Up to now there has been no follow up on this approach.

4. DEVELOPEMENT OF GENETIC ALGORITHM USED

Starting point was the developed executable model of a cancer treatment center, shown in figure 1 (Kühn 2006, Salzwedel et. al. 2007).

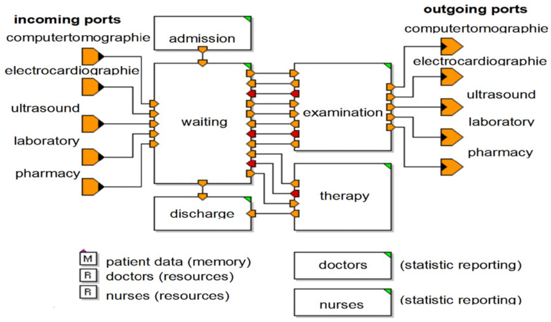

Figure 1: Level 2 Model of cancer treatment center

For purposes of model devellopment and validation real system data were collected. The real data database was split up in two parts. One part was used to develop the simulation model and the other to validate it and to quantify the model error probability. The Model deviation was measured by scheduling time and waiting time for all simulated patients in a defined number of simulation runs. Scheduling time deviated in average -0.7% and waiting time -4.0% compared to the data collected in real system (Kuehn 2006, p.71). Simulation of the existing process clearly shows underutilization of all resources. Analyzing potential improvements showed the greatest potential in scheduling patients based on expected treatment time.

Until now determination of the best scheduling of patient treatment relied just on experience and interpretation of simulation results. This paper shows how a process can be automatically optimized using a genetic algorithm. The development of genetic algorithm and adjustment to the specific problems of a hospital environment is described in the following for an example of a cancer treatment center. Figure 2 shows the general sequence of action for a genetic algorithm.

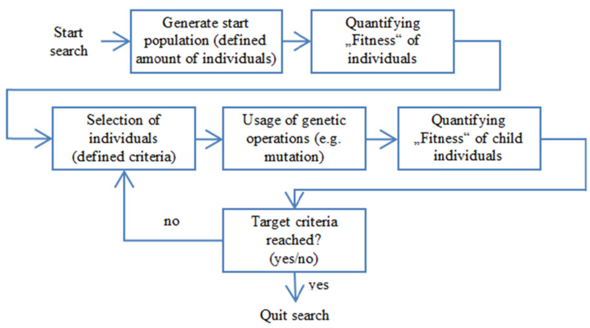

Figure 2: general sequence of action for a genetic algorithm (Pohlheim 2000, p.9)

First, a startup population with a defined number of individuals is generated (parent individuals). In this case 5 individuals are generated randomly. Each individual contains a number of 34 patients with associated treatment plan. This number equals the average of patients treated each day in the cancer center. Every patient has an identification number and an appointment time when he is planned to be treated at the cancer center. In analogy to biology, animals and plants have chromosomes in their cells, which contain genetic material (Gene). Different species can have different numbers of chromosomes. But, for each species the number of chromosomes is the same in every cell. In this example, the cells of each individual contain one chromosome with 34 genes (equals 34 patients). This was implemented as a vector as shown in figure 3.

appointed time	7:30	7:38	7:45	8:14	8:38	9:17 … 11:27	12:17
patient-ID	9	21	33	14	34	10 … 1	34

Figure 3: Layout of an individual

Genes itself contain genetic information (Allele). Within the meaning of optimizing processing time, the appointed time is defined as genetic information. Each gene is labeled with the patient identifier (Patient-ID).

In the next step the fitness function (target function) quantifies the fitness of each parent individual. Therefore every individual is sent through the simulation model of the cancer center. At the end, key properties for each individual are calculated, such as total processing time of the patients and average waiting time per patient. To compare the individuals the fitness function was designed to calculate a benchmark value for each individual. The result is a fitness value for the quality of each individual in order to reduce the processing time and the waiting time of patients. In every fitness test, the best fitness value computed at that time is compared with the current fitness value. If the current fitness value is better than the values reached, the individual and the current fitness value are saved in a file as shown in figure 6.

The fitness function is designed as follows:

Collection of required data

- Calculation of accumulated waiting time of all patients of an individual: (begin taking blood sample – end of admission) + (begin of examination – end of taking blood sample) + (begin of therapy – end of examination) + (discharge – end of therapy is calculated).
- Calculation of accumulated processing time of all patients of an individual: discharge – arrival time is calculated.
- Calculation of processing time fitness:
  (1000 - accumulated processing time / number of patients) / 1000
- Calculation of waiting time fitness:
  (500 - accumulated waiting time / number of patients) / 500)

Calculation of individual fitness

- Calculation fitness of an individual: processing time fitness x processing time loading (= 0.5) + waiting time fitness x waiting time loading (= 0.5)
- If discharging last patient of the individual is at a simulation time (minutes passed from opening of cancer center) less than 250 the fitness value is set to 0.
- If discharging last patient of an individual is at a simulation time greater than 540 the fitness value is multiplied by 0.1.

So fitness values can be between 0 and 1. Best individual values between 0.45 and 0.87 were documented.

Following the general sequence in Figure 2, the next step is to select parent individuals based on their fitness value (Selection). One child is generated out of two parent individuals. Selection is a genetic operator, which controls the search direction in the search room. It determines which parents can pass their genetic attributes to a child. Individuals with better genetic material (higher fitness value) are more likely selected. During several iterations, the children population converges to an optimum. To prevent stagnation at a local optimum, it is important to keep population variety sufficient and genetic material diverse. Therefore, parent individuals with low fitness value also need to be selectable. This keeps the population "alive".
In our algorithm, this is realized through normalization of fitness values of each individual of a parent population. Based on this, individuals are selected randomly. Thus, individuals with high fitness are more likely selected and individuals with low fitness can also be selected.

Furthermore, a parent individual can be used as child individual without any genetic changes. In the current case this is related to the so called "Reproduction". Reproduction rate defines the likelihood that a parent individual is used as child individual.

In addition, children individuals can be an output of a genetic operator "Recombination". Within evolution theory Recombination (Crossover) of genetic information is located between Selection and Mutation regarding to its contribution to achieving the optimum. Recombination means exchanging selected genes of two individuals. Thus genetic information is being passed. In order to do this, a crossover point for both individuals is selected randomly, as shown in figure 4a (vertical line). At the selected point the parent individuals are split into two parts.

	part 1			part 2				
appointed time	7:30	7:38	7:45	8:14	8:38	9:17	11:58	12:17
patient-ID	8	4	1	5	7	2	3	6
appointed time	7:44	7:58	8:12	8:55	9:31	10:19	12:02	12:10
patient-ID	3	1	8	6	2	4	5	7

Figure 4a: Genetic operation "Crossover" - parents

Crossover here relates to alleles (appointed time). Thus the areas to the right of the vertical line of each parent individual are exchanged. The grey marked areas are the areas of exchange. Out of these two child individuals are formed as shown in figure 4b. This form of Crossover is called "Shuffle Crossover" (Nissen 1997, p. 54-56). One outcome can be that the appointed time of two patients is the same after crossover. For example the appointed time of Patient 1 and Patient 3 is 8:12 a.m. This is the case when two or more patients arrive at the same time in a clinic or the appointed time is the same, because of different treatments.

appointed time	7:30	7:38	7:45	8:55	9:31	10:19	12:02	12:10
patient-ID	8	4	1	5	7	2	3	6
appointed time	7:44	7:58	8:12	8:14	8:38	9:17	11:58	12:17
patient-ID	3	1	8	6	2	4	5	7

Figure 4b: Genetic operation "Crossover" - children

Mutation, which is used as third genetic operator, is an undirected process. It is used to get new genetic information. Totally new individuals can be created, which Crossover can't provide. This causes the population variety to increase. New variants and so eventually better individuals and better solutions for the focused problem are possible, which may otherwise never come out of existing populations. This method is also used to overcome local maxima and prevent a stop in a search for a maximum, like it is the case in "Hillclimbing" (Gerdes et. al. 2004, p.25).
For the example of a cancer center, mutation means: A randomly selected new value between opening hours and closing time of the cancer center is set as new appointed time for an patient of an individual, as shown in figure 5.

Individual before Mutation

appointed time	7:30	7:38	7:45	8:14	8:38	9:17	11:58	12:17
patient-ID	8	4	1	5	7	2	3	6

Individual after Mutation

appointed time	7:30	10:15	7:45	8:14	8:38	9:17	11:58	12:17
patient-ID	8	4	1	5	7	2	3	6

Figure 5: Genetic operation „Mutation“

The grey marked area with value of 10:15 a.m. is set as the new appointed time instead of 7:38 as it was before.

So far, several genetic operations are mentioned. Each operation has its own variable that can be changed by a user and gives an input to the model regarding its likeliness to be processed. For the optimization of the cancer center, the following probabilities produced the best optimization results:

- Crossover: 0.3
- Reproduction: 0.7
- Mutation: 0.4

This looks like a high mutation rate. However, only one gene is mutated in this case. This is necessary to produce new appointed times of patients and achieve the necessary flexibility of the algorithm.

After all child individuals have been generated, they are rated by the fitness function, as described before.
The simulation loop will be executed until an exit criteria is reached. This can be a number of loops, elapsed time or a specific value of fitness. In our example the simulation time is limited to 12 hours (overnight run). In this timeframe more than 1000000 loops where done in each run.

The optimization loop, the data link for interaction between genetic algorithm and the model of the cancer center are shown in figure 6.

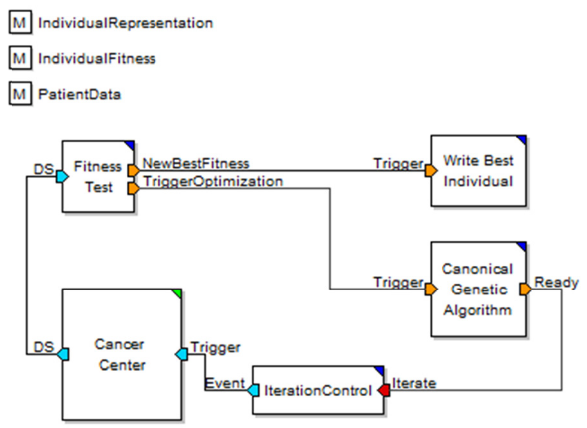

Figure 6: Optimization loop

By doing so the hospital process model becomes a component of this new model as well as the optimization algorithm and fitness function.

5. SUMMARY AND OUTLOOK

It was shown how genetic algorithms can be applied to optimize processes in hospitals. For an example of a cancer treatment center the waiting time was reduced up to 40%. By analyzing the simulation results, a group of patients was identified and summoned in order to be treated at early opening hours of the cancer center. For another group of patients the optimization model planned the treatment between the times of 11:00 a.m. and 01:30 p.m. In addition this group was planned in remaining time slots in the morning until 11:00 a.m. This automated optimization utilizing genetic algorithms confirmed the results in (Kühn 2006) made by expert analysis of simulation results. Thus the applicability of genetic algorithms for optimization of hospital processes could be validated. The optimization results were translated into handling instructions for the cancer center and realized in daily work. These handling instructions lead to nearly equivalent results in practical use as simulated in advance. Currently, this work is extended to scheduling of patients in multi department hospital processes.

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