Proceedings of the 2001 Winter Simulation Conference
B. A. Peters, J. S. Smith, D. J. Medeiros, and M. W. Rohrer, eds.

MULTI-OBJECTIVE SIMULATION OPTIMIZATION FOR A CANCER TREATMENT CENTER

Felipe F. Baesler

Departamento de Ingeniería Industrial
Universidad del BioBio
Av. Collao 1202, Casila 5-C
Concepción, CHILE

José A. Sepúlveda

Department of Industrial Engineering
and Management Systems
University of Central Florida
P.O. Box 162450
Orlando, FL 32816-2450, U.S.A.

ABSTRACT

This paper presents a case study application of a cancer treatment center facility. A simulation model was created and integrated to a multi-objective optimization heuristic developed by the authors with the purpose of finding the best combination of control variables that optimize the performance of four different objectives related to the system. The results obtained show that the implementation of the proposed solution could improve the four objectives in comparison to the existing solution.

1 INTRODUCTION

Most of the applications of simulation optimization have been single objective problems. In the literature there are few attempts to solve multi-response simulation optimization problems. The majority of them are focused on response surface methodology, utility theory and interactive procedures where the decision-maker interacts with the model and leads the search. The major drawbacks of these approaches are local optimality and in most cases the lack of automated direct search.

Here we present a new methodology developed by the authors that is able to find stochastically a global optimum, at least in theory, for a multi-response simulation optimization problem. This approach was used to optimize a simulation model that was developed for a cancer treatment center facility.

2 BACKGROUND

Simulation is an excellent and flexible tool to model different types of environments. It is possible to find in the literature several simulation experiences in healthcare. For example, Garcia et al. (1995) present a simulation model focused on reduction of waiting time in the emergency room of Mercy Hospital in Miami. Pitt (1997) presents a simulation system to support strategic resource planning in healthcare. Lowery (1996) presents an introduction to simulation in healthcare showing very important considerations and barriers in a simulation project. The steps of an animated simulation study oriented to a healthcare situation are presented by Ledlow et al. (1999). All these studies are simulation projects not oriented to the system optimization. One case in this area is presented by Brady and McGarvey (1998). They report the utilization of simulation for the optimization of staffing levels in a pharmaceutical laboratory. In the field of multi-objective simulation optimization there are no attempts related to the health care industry. Going even further, the literature shows just few attempts to solve this problem in general. Some approaches found in the literature are presented next.

Rees, Clayton and Taylor (1985) proposed a procedure for obtaining satisfactory solutions to multiple response simulation models using modified response surface methodology within a lexicographic goal programming framework. The most preferred goal is optimized first using the response surface approach. Then, an attempt to achieve the next highest ranked goal is made without violating the result obtained for the highest ranked goal. In other words, the achievement of the next goal cannot be made at the expense of the higher goal. The same procedure is repeated for each one of the goals.

Mollaghasemi, Evans and Biles (1991) present an aggregation approach for multi-response simulation optimization. The method uses a multi-attribute value function representing the decision-maker preferences. Then, a gradient search technique is used to find the optimum of the assessed function. Mollaghasemi and Evans (1994) proposed a modification of the multi-criteria mathematical programming technique called STEP method. This technique works in interaction with the decision-maker who is asked, in each iteration, to identified the least satisfactory performance measure, which is then improved at the expense of other responses using a gradient search method.

Teleb and Azadivar (1994) proposed an algorithm based on the constrained scalar simplex search method. The method works by calculating the objective function value in a set of vertices of a complex. The method moves towards the optimum by eliminating the worst solution and replacing it with a new and better solution obtained by connecting the old point to the centroid of the remaining vertices. The process is repeated until a convergence criterion is met.

Mollaghasemi (1994) presents an interactive approach for optimizing multi-response simulation models based on the Geoffrion-Dyer-Feinberg (GDF) vector maximal algorithm. In this approach the decision-maker is asked to determine the tradeoff ratios between a reference criterion and the remaining responses. This information in addition to the gradient estimate of each response is used to formulate a directional sub problem that after solving it will lead to the determination of the optimum direction. The process is repeated until the decision-maker is satisfied with the solution.

Boyle (1996) presents a method called Pairwise Comparison Stochastic Cutting Plane (PCSCP). This method combines features from interactive multi-objective mathematical programming and response surface methodology. The method works by finding the center of the feasible region in the decision space and performing a design of experiments centered at that point. Interaction with the decision-maker and cutting plane based techniques are used to determine the most preferred experimental point. Finally, formulating a new constraint based on the estimated gradient reduces the feasible region in the decision space. The process is repeated until the best compromise solution is found or terminating criteria are met.

3 SYSTEM DESCRIPTION

This section presents the description of the cancer treatment center under study. This study was twofold. The first objective was to model, analyze and improve patient flow processes and increase capacity in the main facility. A simulation model of the complete system was created and used to compare different layout alternatives as well as providing a tool for evaluating the impact of alternate scheduling procedures. A second and perhaps the primary objective was to translate this model to a new building which was being designed. A complete description of the system as well as the results obtained in this project is presented in Sepúlveda et al. (1999).

The simulation model of the new building constructed in that project was used to perform a multi-objective optimization and the results obtained are presented in this paper. A brief description of the system giving more emphasis in the aspects that are relevant for this application are presented next.

The M. D. Anderson Cancer Center Orlando (MDACCO) is a full-service cancer treatment facility wholly-owned by Orlando Regional Health Systems. There are two processes that take place there. The first process is referred to as medical oncology (MO). During this process patients go to the facility to consult a medical doctor. This process takes place on the second floor of the building. The second process is the ambulatory treatment process (ATC). Patients go through the ATC process to get treatment that lasts less than eight hours. During this process the patients receive chemotherapy sitting in chairs that are located at the forth floor of the building.

The patients were classified into four types based on the sequence of activities that they go through once they are at the medical facility. These patients are identified as medical oncology, ambulatory treatment center, injection and pre- processed patients.

3.1 Medical Oncology

These patients are all scheduled and they arrive by appointment time. After drawing blood on the first floor, Medical Oncology patients take the elevator to the second floor. Here patients check in and wait to be seen by a doctor. After the exam patients go to the co-pay area and either leave the building or go to ATC depending on a doctor's decision.

The resource availability in MO is 5 receptionists and co-pay personnel (double function), will have with 22 exam rooms served by 11 doctors and 11 nurses. Extrapolating from the original situation and considering the increase in resources, an assumption of 176 patients per day has been made.

3.2 Ambulatory Treatment Center

These patients are all scheduled and they arrive by appointment time. Some walk-in patients are received coming from MO. After having blood drawn in the first floor, ATC patients take the elevator to the fourth floor. Patients check in and wait until their drugs are ready and a treatment chair becomes available. After this, patients start treatment on a chair and leave the building after the treatment is finished.

The resource availability in ATC is 34 treatment chairs, 2 shoot rooms, 2 LPNs, and 8 nurses. Extrapolating from the original situation and considering the increase in resources, an assumption of 58 patients per day has been made.

3.3 Injection Patients

This type of patient goes to ATC just for an injection and stays for about fifteen minutes. They do not use the treatment chairs. These patients are all scheduled and they arrive by appointment time. The patient goes to the treatment center for either an injection or fifteen-minute treatments. They go directly from the waiting room to the injection chair where the lab technician will take care of them. If the lab technician is busy the patient will be treated by a nurse.

3.4 Pre-Processed Patients

Some of the patients that go to ATC have already been seen the day before and they have the blood drawn and analyzed prior to the visit. Because drugs and blood results are available upon arrival, the patient goes directly to treatment chairs after check-in. This streamlined process is constrained only by chair availability or unusual circumstances encountered in drug preparation.

3.5 Pharmacy

The Pharmacy is located on the fourth floor. Its function is primarily to prepare drugs for the ATC patients. The preparation is made based on the blood analysis information received from the laboratory.

When a drug preparation request arrives, it is processed as soon as a pharmacist or technician become available and no other requests were waiting. The pharmacy has two pharmacists and two technicians. A maximum of four drugs can be prepared at the same time.

3.6 Laboratory

The Laboratory is located in the first floor of the building and this is the first stage of the process. Patients arrive and check in, then wait until a room becomes empty in order to draw blood. After drawing blood the patient leaves the floor and takes direction to the final destination (ATC, MO). The blood specimen is analyzed and reported to its final destination, Pharmacy or MO. The resource availability in the laboratory is 1 receptionist, 6 chairs for drawing blood, 1 port room, 5 lab technicians and 1 double capacity machine.

4 METHODOLOGY

This section presents a brief description of the methodology developed by the authors to solve multi-response simulation optimization problems. This methodology integrates simulation, goal programming, and genetic algorithms. The simulation model serves as a black box representing the objective functions of the problem, which generates output responses for all the objectives involved in the analysis. These outputs are transformed using a goal programming framework enabling to consider all the objectives during the optimization process. The genetic algorithm is responsible for performing the search for improved solutions. The selection process of the GA is performed using a multiple comparisons statistical technique. In this way, the stochastic nature of simulation is considered when a selection among different scenarios takes place.

A complete explanation of the methodology and a detailed description of each step is presented in Baesler (2000) and Baesler and Sepúlveda (2000). Just a brief description is presented in this paper. The general structure of the methodology can be divided in nine major sections, each one containing subsections. Figure 1 shows a diagram of the methodology.

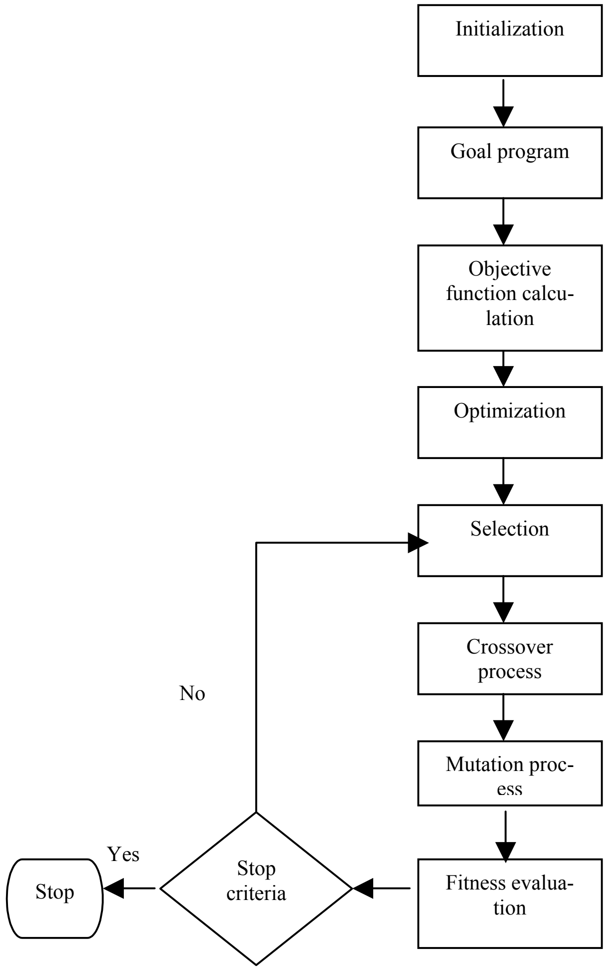

Figure 1: Methodology Chart

The first section or step of this methodology (initialization) is related to the definition of the initial conditions of the problem. This information can be divided in two groups; information related to the problem itself, and information required by the genetic algorithm. In this step all the variables, objectives, goals and constraints have to be defined. In the same way the definition of the genetic algorithm parameters, such as, crossover and mutation rate, population size, etc. has to be done. Following this step, a goal program has to be created. More details about goal programming can be found in Ignizio (1976). This model minimizes the difference of the expected value of the simulation output for each objective and the corresponding goal defined by the decision maker. Using this model, an integrated measure of effectiveness considering all the single objectives can be obtained. After running each scenario, the results obtained are transformed using the goal program. This new value will serve as the objective function number that has to be improved in order to find a better solution to the problem.

The next step is the objective function variance estimation. Since simulation is a stochastic technique, it is necessary to capture the randomness associated to it and include it in the objective function. A simulation model is able to generate the mean and the variance for each one of the objectives associated with the problem.

The first stage to start the optimization process is to generate an initial population of solutions (scenarios). The number of point estimations required to start is equal to the population size parameter defined in the initialization step of the methodology. The selection of these scenarios is carried out randomly. The reason for this is to cover a wide range of the surface response. After running all the scenarios, the mean and variance for each MOE considered in the analysis have to be collected. This information is used as input for the goal program in order to obtain the integrated objective function value.

The following sections in the methodology are related to the sequence of steps required by the genetic algorithm heuristic, selection, crossover, mutation, fitness evaluation and stopping criteria. These steps present no major difference in relation to any genetic algorithm application. An introduction to this technique with a focus in engineering applications can be found in Gen and Cheng (1997). An important difference in the genetic algorithm section of this methodology is presented in the selection step. This task was modified in order to consider the stochastic nature of the simulation output.

5 CASE STUDY

The following section presents the results obtained after using the proposed methodology in the cancer treatment center problem presented before. In this particular situation four control variables and four different objectives were selected for the problem. Table 1 shows the control variables and the upper and lower limits for each variable. Table 2 shows the four objectives with the corresponding goals and weights that were selected by the decision makers involved in the analysis. Table 3 presents the genetic algorithm parameters used in the problem.

Table 1: Control Variables

Control Variables	Limits
Number of Treatment Chairs at ATC	25-40
Number of Drawing Blood Nurses	4-10
Laboratory Capacity (Personnel, Equipment)	2-6
Pharmacy Capacity (Personnel, Equipment)	2-6

Table 2: Objectives

Objectives	Goal	Weight
Minimization of Patient's Waiting Time	120 Mins.	0.20
Maximization of Chair Utilization	95 %	0.30
Minimization of Closing Time	480 Mins.	0.20
Maximization of Nurses Utilization	85 %	0.30

Table 3: Genetic Algorithm Parameters

Genetic Algorithm Parameters	Value
Population size	12
Crossover Probability	1.00
Mutation Probability	0.05

After defining all the information needed by the methodology, an initial population of 12 scenarios (chromosomes) was created. The results obtained after running these scenarios is presented in Table 4.

Table 4: Initial Population

Scenario	Time	Chair	Close	Nurse	Fitness
250744	215	0.82	722	0.44	0.519
341022	212	0.62	718	0.31	0.620
260642	232	0.74	733	0.50	0.558
290925	170	0.77	654	0.37	0.440
380632	192	0.53	698	0.52	0.524
370532	205	0.56	719	0.62	0.513
280842	228	0.72	727	0.38	0.598
290552	213	0.70	710	0.63	0.479
400532	203	0.52	719	0.62	0.523
270923	195	0.77	692	0.35	0.509
320462	209	0.63	696	0.81	0.424
290926	166	0.76	654	0.37	0.434

This means that for chromosome (scenario) 250744 (25 chairs, 7 nurses, 4 lab personnel, and 4 pharmacy personnel) the results of simulating 70 replications was an average of 215 minutes of waiting time, 82% of chair utilization, 722 minutes of operation, and 44% of nurses utilization. This combination of individual results yields to a fitness value of 0.519. The optimization process went though 13 generations until converged to four chromosomes that are phenotypically almost equal but with genotypical differences. Table 5 shows the results of generation 13.

If we compare the average fitness value of the initial population (0.512) with the last generation (0.235) it is possible to appreciate an improvement of approximately 54 percent. Since this is a minimization problem a smaller fitness value represents a better solution. Figure 2 shows the evolution of the average fitness value from the initial population until the last generation.

Table 5: Last Generation Results

Scenario	Time	Chair	Close	Nurse	Fitness
390524	125	0.64	585	0.76	0.226
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390524	125	0.64	585	0.76	0.226
390524	125	0.64	585	0.76	0.226
400544	126	0.63	588	0.76	0.230
400544	126	0.63	588	0.76	0.230
350524	138	0.70	598	0.75	0.241
350524	138	0.70	598	0.75	0.241
350524	138	0.70	598	0.75	0.241
350524	138	0.70	598	0.75	0.241
400523	131	0.61	587	0.76	0.247
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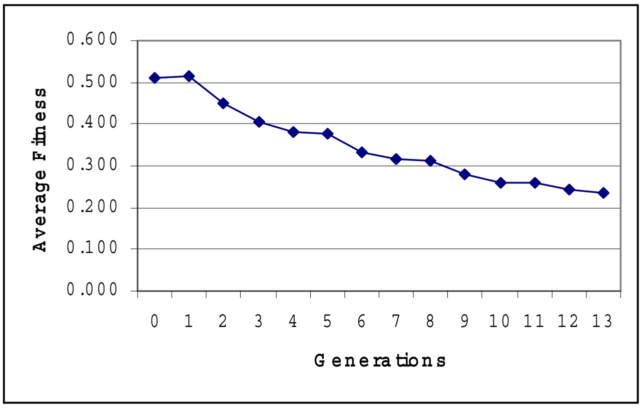

Figure 2: Average Fitness Plot

This plot shows the decreasing trend presented by the average fitness value. The plot starts with a value of 0.513 in the initial population and decreases until a value of 0.235 in generation 13. The next plot shows the evolution of the best individual solution found within each generation during the whole process.

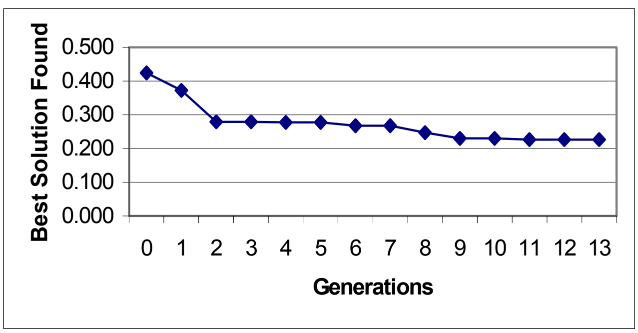

Figure 3: Best Solution Found Plot

The total number of possible combination for this particular problem is 2,800. The methodology explore a total of 73 different scenarios, this represents 2.6 % of the whole solution space.

6 RESULTS

In order to analyze the methodology results, a comparison to the "as is" situation in the cancer treatment center was performed. The system configuration for the existing alternative is as follows:

- 34 treatment chairs
- 6 nurses for drawing blood
- Capacity to analyze 2 blood samples at the same time in the laboratory. This is equivalent to capacity 2
- Capacity to prepare 4 drugs at the same time in the pharmacy. This is equivalent to capacity 4.

Table 6 shows the results of the simulation model after running this scenario. The table also shows the results of the four chromosomes obtained by the methodology.

Table 6: "As Is" Scenario and Last Generation Results

	Scenario	Time	Chair	Close	Nurse	Fitness
As Is	340624	145	0.71	602	0.61	0.301
1	390524	125	0.64	585	0.76	0.226
2	400544	126	0.63	588	0.76	0.230
3	350524	138	0.70	598	0.75	0.241
4	400523	131	0.61	587	0.76	0.247

From this table we can appreciate that all the solutions generated with GA have a better fitness value than the *As Is* scenario (solution adopted by the DM for this situation). The fitness of scenario number 1 is a 25% lower than the existing solution, and for scenario number 4 the improvement is an 18%. So, if we want to decide using the fitness value, any of the suggested solutions are better than the existing one. The same analysis can be done for each one of the individual objectives. The *As Is* scenario presents a worse solution for all the objectives except for chair utilization which is only matched by scenario number 3. Since scenario one dominates scenario two in all the objectives as well as the fitness value, and scenario two is more "expensive" because requires 40 chairs instead of the 39 of scenario one, we can eliminate it from the analysis.

The final selection of the best alternative has to be done by the decision-maker considering the convenience and feasibility of the implementation of the solution. However, we can suggest an answer from our point of view. If we consider that a chair utilization of 70% is not significantly different to 71%, scenario number 3 is the only one that dominates or at least matches all the objectives of the existing solution. Even though the improvement on the first three objectives is not too significant, the difference in the last one, nurse utilization, is very important. Another important issue is related to the cost of the implementation of this alternative. Of all the solutions this one is the least costly because it requires just 35 chair instead of 40 and 39. The implementation of this solution would require adding just one more chair to the system and decreasing the number of nurses to five. It is important to mention that the number of chairs, as well as all the other control variables is independent to the number of patients that arrive to the center every day. In other words, an alternative that considers 40 chairs does not mean that will give treatment to more patients than an alternative that considers just 35 chairs.

The table also shows that all the suggested alternatives have five nurses. The same happens with lab and pharmacy capacity 2 and 4 respectively for almost all the alternatives. This suggests that the best solution should consider that configuration. This leaves just the number of treatment chairs for selection. For that reason 35 chairs appear to be a reasonable number.

The results obtained in this section represent a single decision-maker personal view of the problem. Since the goal programming objective function used in the model was constructed using DM information, the results obtained might change if a different DM were selected for the analysis. From all the information gathered to construct the model, the most important piece are the weights associated to each objective. These weights represent the relative importance of each one of the objectives, so a different DM could select a different combination of these values. This could lead to a different solution to the problem and another scenario would be suggested for implementation.

7 CONCLUSIONS

This paper has presented a case study of a cancer treatment center problem. In this study a new approach for solving multi-objective simulation optimization problems was applied to the cancer facility. Four control variables and four different objectives were considered in the study. The resulted solutions were compared to the existing configuration of the system. All the alternatives generated by the methodology are better in terms of it fitness value than the *As Is* situation. The level of improvement of these solutions ranges from 18 to 25 percent.

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AUTHOR BIOGRAPHIES

FELIPE F. BAESLER is a Professor in the Departamento de Ingeniería Industrial of the Universidad del BioBio, Chile. He received his Ingeniero Civil Industrial degree from the same university in 1993 and a M.Sc. (1998) and a Ph.D. (2000) in Industrial Engineering from the University of Central Florida. His research interests are simulation optimization, artificial intelligence and healthcare simulation. He is a member of the Institute of Industrial Engineers. His e-mail address is <fbaesler@ubiobio.cl>.

JOSÉ A. SEPÚLVEDA is Associate Professor in the Department of Industrial Engineering and Management Systems Department at the University of Central Florida. He received his Ingeniero Civil Químico degree from the Universidad Santa María, Valparaíso, Chile, in 1970. From the University of Pittsburgh he received a M. S. degree in Industrial Engineering in 1972, a Master in Public Health degree in 1974, and a Ph.D. degree in Industrial Engineering in 1981. Dr. Sepúlveda is a registered Professional Engineer in Florida (1983) and Chile (1975). He is a member of the Institute of Industrial Engineers, the Society for Computer Simulation, the Institute of Management Sciences, the American Public Health Association, and the Hospital Information Management Systems Society. His e-mail address is <sepulved@mail.ucf.edu>.