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Simulation-based Optimization in the Automotive Industry – A Case Study on Body Shop Design

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In the automotive industry, a new body shop production-line needs to be set up for almost every new car model. Due to the relatively short product life cycles, the planning process of body shops can almost be regarded as continuous. A main problem is to find an efficient layout fulfilling the desired production rate which is characterized by small buffer sizes and optimized cycle times. Often, the optimization of a new body shop is carried out manually, possibly supported by a simulation model to analyze the impact of different cycle times and buffer sizes. In this paper, we present a mathematical formulation and an automated optimization approach for this planning problem. The optimization modules, which have a direct interface to the underlying simulation model, are based on metaheuristics, such as genetic algorithms and simulated annealing. Here, the main task lies in comparing the manual body-in-white configuration with metaheuristic-based optimization approaches. For an evaluation of the potentials of our approach, a case study was carried out in collaboration with a German car manufacturer.

Keywords: Body shop design, automotive industry, simulation-based optimization, genetic algorithms, simulated annealing

1. Introduction

Within the car body shop of an automotive plant, the body-in-white is assembled from pre-formed pieces of metal. Here, up to one hundred or even more welding robots and various other equipment are needed to complete the body-in-white before it is conveyed to the next step of the production process. Since the body-in-white of a new model is typically significantly different from the previous type of car, manufacturers have to design a new body shop for almost each new model. At the same time, product life cycles in the automotive industry become continuously shorter and the investments for the equipment sometimes exceed one hundred million dollars. Of course, the amount of money spent on equipment mainly depends on the flexibility of the overall manufacturing system, but both the efficiency of such planning processes and the quality of the final design are also essential for a company's success.

In the early conceptual design, being among the first steps of the planning processes, the shop is divided into 12 to 18 different blocks, each representing a welding area covering numerous welding operations in different stations. To decouple the production process, buffers are usually introduced between two subsequent blocks forming a structure of blocks and buffers. Here, a converting topology can be observed,

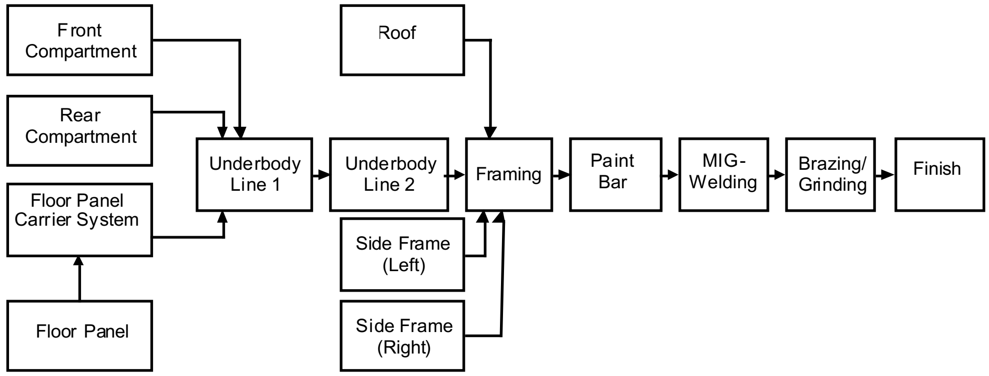

Figure 1. Conceptual design of a car body shop

as the assemblies and subassemblies coming from certain blocks meet in succeeding areas. For instance, the car underbody, the roof and the side frames are assembled in a so-called framing line. The structure of the body shop considered in the case study is shown in Figure 1.

Over the last couple of years it has become state-of-the-art to support the early stages of the conceptual design with simulation models using commercial tools like Automod, SIMPLE++, or Witness [1-4]. The optimization of buffer sizes and cycle times, while maintaining a demanded production rate of the body shop, are well-known applications of discrete event simulation studies [3]. However, simulation does not improve a given solution by itself. Instead, it can only be regarded as an efficient tool to analyze a given solution.

Concerning the optimization of a body shop concept, two parameters describing each block are of interest: the cycle time, i.e., the time for completing one cycle of operations within the block, and the availability of the block. Note that achieving *long* cycle times and maintaining a desired production rate is important for the next step within the planning process, where the blocks are designed in detail and relatively long cycle times may allow a reduction of necessary resources, e.g., the number of robots used for the same activities.

The search for a good solution (good in terms of small buffers and long cycle times) is usually conducted manually starting with solutions based on analytical calculations and experiences of the planning engineers. Subsequently, these solutions are iteratively improved by changing buffer sizes and cycle times systematically and conducting a simulation experiment for each set of parameters. However, the growing number of concept studies puts a constant pressure on all car manufacturers to increase the quality and the efficiency of the planning processes. In this context, the automation of this optimization process may provide better results, even though it is difficult to find applications of simulation-based optimization in the automotive industry in the related literature [5].

But the successful application of simulation-based optimization to other real world problems, along with the availability of commercial packages, has led to the idea of adapting these methods for the automotive body shop design problem. The aim of this paper is to test and evaluate the combination of body shop simulation models and modern optimization methods, especially metaheuristics as genetic algorithms and simulated annealing.

To exemplify the potentials of our approach, a comprehensive case study has been undertaken at the BMW AG, Munich. Here, existing simulation models of an already manually planned body shop were combined with two available optimization packages offered by vendors of simulation tools, the Witness-Optimizer (a simulated annealing-tool) by Lanner Group and SIMPLE/GA (a genetic algorithm-component) by Tecnomatix.

In the following section, we discuss the body shop design problem in greater detail. Then, we present our approach of combining metaheuristics and simulation models, as it has been developed and tested for the presented case study at BMW. Here, we also give a short review of similar models and metaheuristic-based solution procedures proposed in the literature. In Section 4, we discuss the experiments performed and some computational results. Section 5 provides some conclusions and directions for further research.

2. Problem Description

The production of a body-in-white follows a scheme that is almost the same throughout the automotive industry. The main steps of the production process differ only slightly between different manufacturers and car models. Generally, a given number m of blocks are part of the body shop concept, where manual labor and robot processes are organized. After the elements of the underbody (four subassemblies in our example, cf. Fig. 1) have been produced in the respective blocks, they are combined and welded in the following two blocks. Then, the side frames and the roof are attached to the underbody forming the body frame. In our example, a paint bar is fixed to the body frame in the next block. The paint bar supports the body transportation inside the paint shop, but it is not part of the completed car and is removed again later in the assembly process. Afterwards, brazing and grinding activities are carried out. In the finish area, the doors, the trunklid, and the hatch-back are attached. The finished body-in-white then leaves the body shop and is conveyed to the paint shop.

Major problems in the production process are breakdowns that occur randomly in the blocks, e.g., due to robot failures. The time of such breakdowns disperses strongly in the real-world. The *mean time to repair* (MTTR) and the *mean time between failures* (MTBF) define the availability of each block s with $s \in \{1, ..., m\}$:

$$Availability_S = \frac{MTBF_S}{MTBF_S + MTTR_S}$$

To avoid a breakdown in one area that would lead to a stop of production in other areas, buffers are introduced to de-couple the blocks. However, large buffers do have several disadvantages [6]. Considerable investments are necessary to install buffer space in an automotive plant. These investments are even outnumbered by the costs for day-by-day operation and maintenance of the buffers. Furthermore, buffers require space and they enlarge the *overall cycle time* of the production. Thus, one objective of the body shop design is to minimize buffer sizes.

In a highly automated system, like a car body shop, cycle times might be expected to be constant, but they vary from block to block. Note that the *cycle time* in this context is defined as the processing time to finish a series of operations within one block and not as the time of the overall production process (overall cycle time). For the latter, no optimization is possible as the activities cannot be organized in a different block structure due to technical restrictions.

A theoretical upper bound T_S^{max} for the cycle time of block s is given by the availability and by the required production rate of the shop:

$$T_S^{max} = \frac{ProductionTime \times Availability_S}{ProductionRate}$$

A second goal of the conceptual design is to determine a cycle time close to this upper bound for each block, as it leads to the largest possible time to organize the work within the block in the subsequent step of the planning process. Here, a value close to T_S^{max} allows the engineers a relatively high degree of freedom for the detailed design of block s, possibly reducing the amount of equipment – and, along with it, the necessary investments – needed for finishing all activities within the cycle time. If, for example, the body shop is designed to produce 400 units per day within a production time of 1000 minutes and assuming an availability of 90% for the framing area, we obtain $T_{Framing}^{max} = 135$ seconds.

Another cycle time-related target is to obtain (almost) identical cycle times in all blocks. Such balanced cycle times are supposed to have a positive effect on buffer sizes, i.e., the smaller the variance of the cycle times, the less buffer space is expected to be needed.

Based on these considerations, the body shop design problem (BSDP) can be formulated as a multi-objective optimization problem:

- Minimize the overall number of buffer spaces
- Maximize the cycle times for the various welding blocks
- Minimize the deviation of the cycle times, i.e., smooth the cycle times of the welding blocks
- Subject to fulfilling a daily rate of N car bodies to be produced (at an average).

Note that there are situations where the above objectives are of conflicting nature. For instance, in case of different availabilities for the blocks, the third objective is in conflict with the aim of having the longest possible cycle time for each block.

Any solution procedure for the BSDP has to cope with the different objectives. The idea of associating costs with buffer space and cycle times is usually rejected by body shop experts. It is almost impossible to determine cycle time-dependent cost functions that are valid for the great variety of welding sections within one body shop – not to mention the welding sections in different body shops. However, as the metaheuristics under consideration are designed to determine the quality of a solution based on a single value, an objective function that combines cycle times and buffers sizes is introduced in this paper. For this purpose, the maximization of cycle times is transformed into minimizing the difference between the cycle time of each welding block s and its upper bound T_S^{max}.

Given a vector $\overrightarrow{pg}$ with n components (buffer sizes), a vector $\overrightarrow{tz}$ with m components (cycle times), an objective function F comprising the three objectives given above and a function d to calculate the daily production rate of the body shop, we can formulate the BSDP as:

Minimize $\quad z = F(\overrightarrow{pg}, \overrightarrow{tz})$

subject to $\quad d(\overrightarrow{pg}, \overrightarrow{tz}) = N$

with $\overrightarrow{pg} \in Z_+^n,\ \overrightarrow{tz} \in R_+^m, N \in Z_+$

Besides the difficulties in defining an appropriate objective function *F*, problems also occur in determining the daily output $d(\overrightarrow{pg}, \overrightarrow{tz})$, as *d* strongly depends on stochastic variables due to random down times within the welding sections. Thus, a solution procedure for the BSDP needs an appropriate component to calculate *d* and an appropriate procedure to minimize *F*. The following section will discuss different approaches for both tasks.

3. Solution Procedure and Related Research

Queuing theory [7], as well as simulation modeling, may be applied to calculate the daily output *d*. Since simulation as a tool is widespread in the automotive industry, it is obviously very convenient to use a simulation model to compute *d* even though simulation is rather costly in terms of performance – as each evaluation of the objective function requires (at least) one simulation run [8]. Nonetheless, we choose a simulation approach for our solution procedure, mainly because the simulation models to calculate *d* were already given prior to the study. One of the two simulation models of our example was built using the simulation tool SIMPLE++. The animation layout, which corresponds to the block and buffer structure described above (cf. Figure 1), is shown in Figure 2.

A common approach to solve the BSDP is (manually conducted) local search. It can be described as changing a given solution (a parameter setting) stepwise (usually varying only one parameter at a time), and to evaluate the new solution, in our case by executing an entire simulation experiment. This can be repeatedly done until no further improvement can be achieved. However, using such a search technique will often end in a local optimum, that is, the best overall solution has not necessarily been found (cf. Fig. 3). To overcome local optima (and to find the global one) metaheuristics can be applied. These are designed to guide local search heuristics in the search process. In this context, simulation-based optimization approaches that include metaheuristics have also been proposed [9-12].

In the field of metaheuristics, genetic algorithms have empirically proven to be a very efficient approach to control a simulation-based optimization [13]. Genetic algorithms, initially presented by Holland [14], can be understood as an intelligent exploitation of random search [12] and belong to the group of evolutionary algorithms. The name genetic algorithm (GA) is derived from biology, where genetic structures of chromosomes go through an assumed optimization process of selective breeding. A chromosome consists of genes (variables), e.g., the buffers under consideration. An individual or solution is defined by a couple of chromosomes. It is assumed that for each individual, there exists a fitness value which determines the chance for this particular individual to survive and create offspring within a population of individuals. As the size of a population is limited in some way, individuals having a higher fitness are more likely to survive and create offspring. Through a (simulated) evolutionary process of selective breeding, which is based on the principle of survival of the fittest, the average fitness of a population is supposed to increase from generation to generation leading to an optimum (that is still likely to be a local one). Offspring are created by combining individuals, which is simulated by crossover operators. Another operator adopted from biology is the mutation operator which simulates random changes of variable values, maintaining a certain diversity of chromosomes within a given population.

Another metaheuristic under consideration in this paper is simulated annealing (SA). Instead of creating

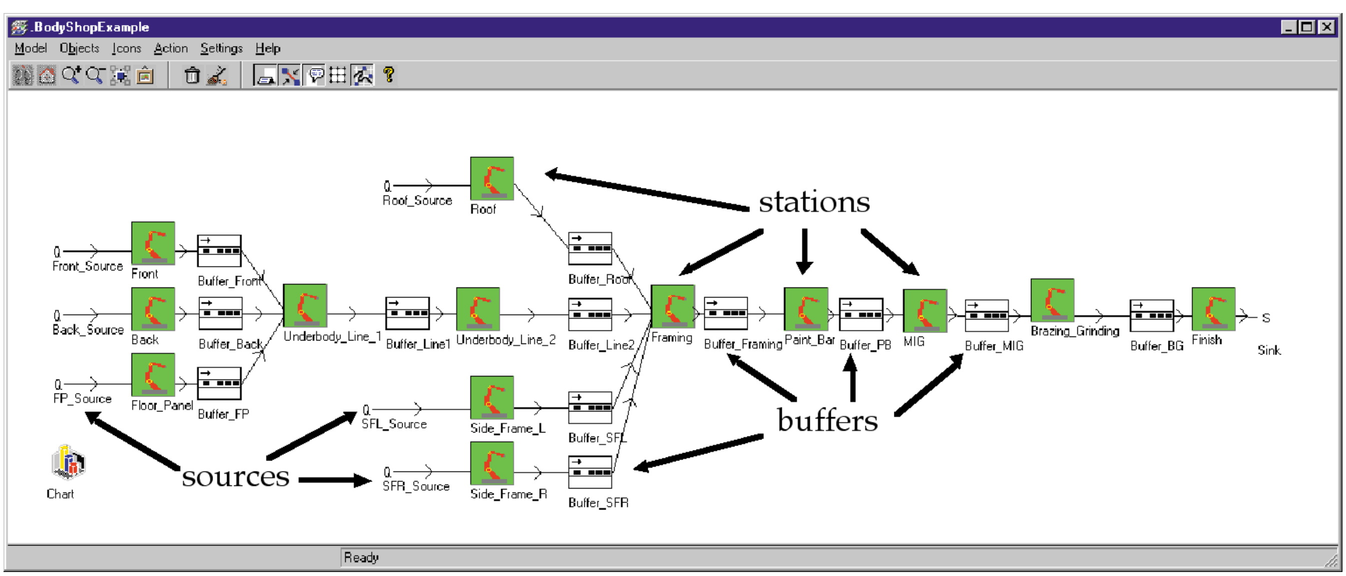

Figure 2. Simple simulation model of a car body shop concept

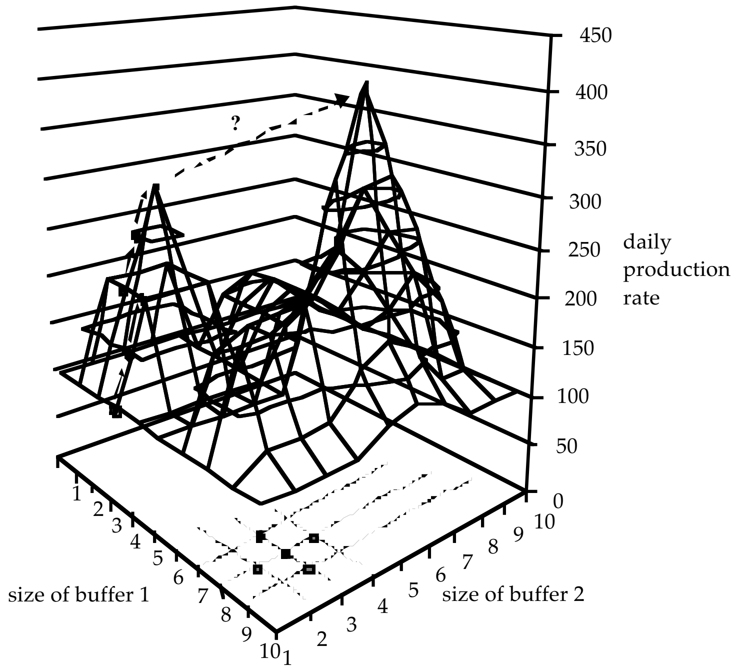

Figure 3. Example for local and global optima

a population of individuals that are combined to create new, hopefully better solutions, only one solution is considered at each iteration. This solution is changed locally. After each computation of a new solution, it is decided whether the new solution should be accepted, even if the solution quality is worse than the one of the original solution. The probability for accepting worse solutions is based on the time the algorithm has been processing (using a cooling table), thereby expecting a convergence to a global optimum.

Combined with a simulation model, GAs have been applied to optimize, e.g., the production rate of a board manufacturing process at a Hewlett Packard plant [13]. The system consists of 21 coupled blocks with some of them working in parallel. A mix of 6 to 14 different types of boards is produced and some types do not have to be operated in all blocks. The cycle times of three within the 21 blocks have been optimized with each cycle time having a range of 32 different values. GAs find the global optimum that was previously calculated using complete enumeration within 15 generations of 30 individuals.

Similar experiences in the field of simulation-based optimization have been obtained, e.g., for generic production systems [15], a bicycle plant [16], industrial robots [17], as well as automated guided vehicles [18]. Other studies consider a combination of discrete event simulation and altered GAs, e.g., a hybrid GA to tackle production planning problems [19] and diverse evolutionary algorithms to optimize a simple sample inventory system, to minimize the inventory of a microwave oven production system, or to optimize a flexible assembly cell with an accumulating transfer system [20-21,9]. Similar approaches concentrate on evolutionary algorithms and an extension of a polyeder approach (so-called complex strategy) to improve a large scale assembly line [22], or even a combination of these two metaheuristics in a simulation model of a chemical plant [23]. Additionally, some work has been conducted to optimize production systems with similar characteristics to a body shop (machinery with random breakdowns and buffers to decouple the machines) using simulation and (approximative) analytical methods [24-25], or to exploit other metaheuristics for simulation-based optimization [27-29].

The interaction between any optimization module and a simulation model can be described as an iterative process: Each solution computed by the optimization module is passed to a control module within the simulation model, e.g., a simple text file using a file interface of the simulation package used. This control module sets the model parameters according to the data represented in the solution and starts the simulation run. After the simulation run is finished, a second control is invoked that calculates the fitness of the individual or the solution quality, respectively, by examining the experimental results. Based on these results, the next iteration is carried out by the optimization module under consideration.

In order to evaluate the solution quality, a function is needed that represents the objectives of the BSDP as discussed in Section 2. Since the GA- and SA-implementations under consideration in this paper do not offer possibilities to check the feasibility of individuals, the corresponding constraint needs to become part of the fitness function. This function can be modeled as a sum of weighted terms [22], each term representing an objective or a constraint. The following fitness function *f* to be minimized was used for the BSDP:

$$f(\vec{pg}, \vec{tz}, d(\vec{pg}, \vec{tz})) = W_1 \cdot \sum_{i=1}^{n} pg_i + W_2 \cdot \sum_{s=1}^{m} (T_s^{max} - tz_s) + W_3 \cdot \frac{1}{m-1} \cdot \sum_{j=1}^{m} (tz_j - \overline{tz})^2 + g(d(\vec{pg}, \vec{tz}), N)$$

The first term punishes growing buffer sizes, the second a deviation of the cycle times from the respective upper bound, whereas the third term increases according to the variance of the cycle times. The last term corresponds to the constraint concerning the production rate. Here, the function *g* has been introduced to distinguish two cases:

$$g(d(\vec{pg}, \vec{tz}), N) = \begin{cases} M \cdot (N - d(\vec{pg}, \vec{tz})) & \text{if } d(\vec{pg}, \vec{tz}) < N \\ 0 & \text{otherwise} \end{cases}$$

If the production rate is not met we obtain a very poor fitness for very large *M*. The weights W_1, W_2, and W_3 of the other terms were determined in discussions with body shop planning experts and set to 1, 2 and 2, respectively, whereas *M* was set to 1200 throughout all experiments described in the following section.

4. Computational Results

The main interest of the case study presented in this section is a comparison of the commercial packages with a manually guided local search, as it is usually performed at BMW. The implementations of both commercial optimization tools need to be considered as black boxes, since the vendors offer compiled modules that can only be configured to some degree by user dialogs (see Figure 4). We additionally compare the results with a Pascal implementation of a simple genetic algorithm with some slight modifications [30-31], to be able to rank and evaluate the commercial packages on a broader basis. This GA is based on a 1-point-crossover, a roulette selection strategy and a generational replacement of individuals. The fitness corresponds directly to the objective function value (instead of using a ranking-scheme).

The real-world problem instance of the BSDP outlined above was provided by BMW. This problem instance was particularly interesting for our research as it has been subject to a prior manual optimization and the results obtained by BMW could be directly compared with the results of our solution approach. The problem instance comprises n = 13 different buffers and m = 14 different welding blocks.

In order to apply simulated annealing, an appropriate way has to be defined to change a solution locally. Here, we decrease or increase the cycle time of one block by one second or the size of one buffer by one unit, respectively, to compute a new solution. The values for all 27 variables have further been limited to 16 possible cycle times and 16 possible buffer sizes to reduce the solution space under consideration. The same variable values and domains were used for the GAs.

Basically, four different approaches to tackle this instance of the BSDP are compared: the manual search procedure (MAN), the SIMPLE/GA module combined with a SIMPLE++ simulation model of the body shop denoted as SGA, the (extended) standard

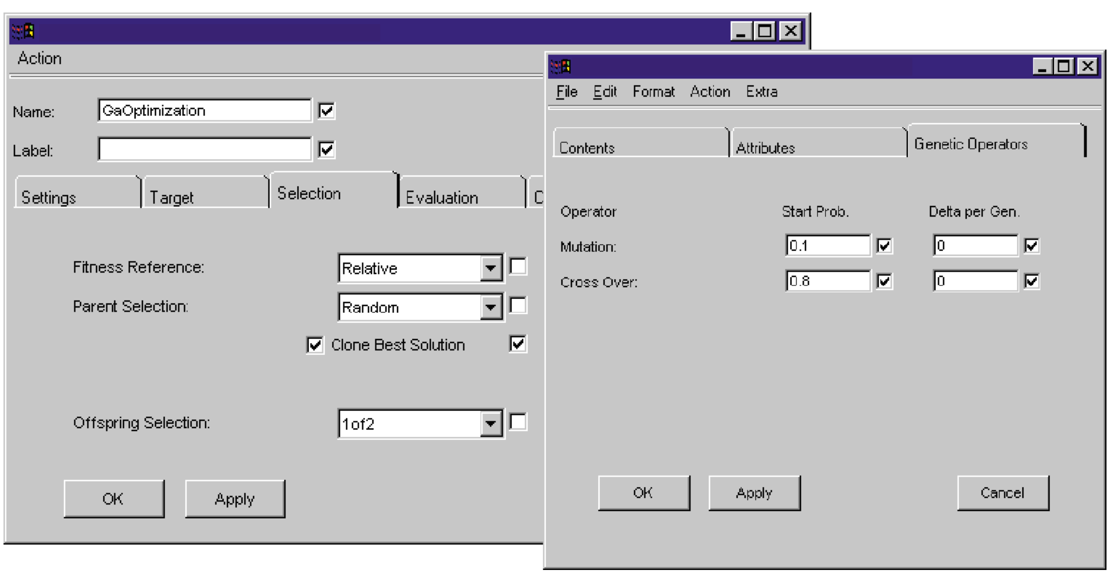

Figure 4. Example of parameter settings for SIMPLE/GA

Pascal implementation combined with a SIMPLE++ simulation model (PGA), and the Witness-Optimizer module using simulated annealing combined with a Witness simulation model of the body shop (WSA). The presented case study comprises the analysis of 45 simulation experiments consisting of more than 20,000 simulation runs. The experiments were conducted on an IBM-compatible PC with an Intel Pentium II microprocessor running at 400 MegaHertz. The tests are divided into three parts. A first series of experiments is performed to provide insights into the steady state and precision of the stochastic simulation model. Based on these theoretically important results, i.e., how to obtain sustainable estimates of the performance measure *d*, a set of experiments is conducted to compare the three metaheuristic approaches with the manual optimization. In a third series of experiments, the impact of the algorithms' calibration is analyzed in more detail, i.e., the parameters that influence the search behavior of the SIMPLE/GA as, e.g., the number of generations, the number of individuals per generation, the probability of mutation and crossover or the applied selection strategy, are under further consideration.

4.1 Experiments – Part I

To gain information about the length of a simulation run necessary to achieve a steady state, plots of the moving averages of the output per hour are examined [32]. Here, the average output is computed of *w* hours, i.e., *w* is the length of the (time) window under consideration and is positive integer. As Figure 5 shows, it takes the body shop model at least 16 hours to reach a state that can be considered as steady.

The calculation of confidence intervals based on the results of the first series of experiments reveals the classical dilemma of stochastic simulation between accuracy of the estimates and computation times. Figure 6 shows the development of the ratio between confidence interval half-length and average daily out-

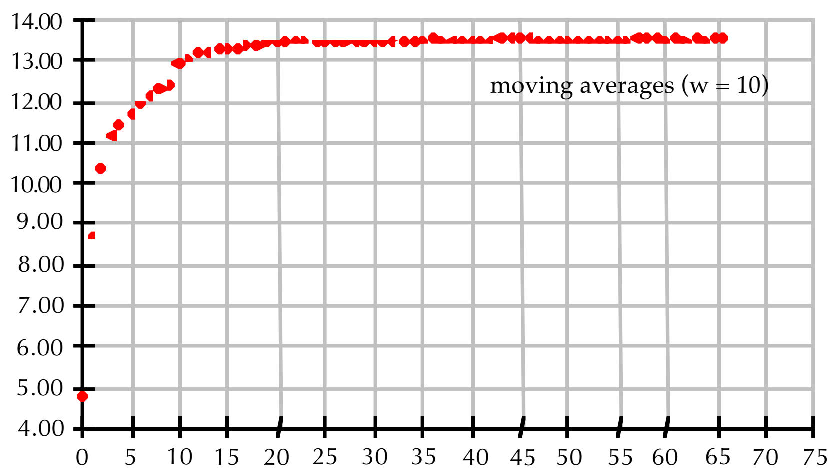

Figure 5. Estimation of the run-in period using moving averages

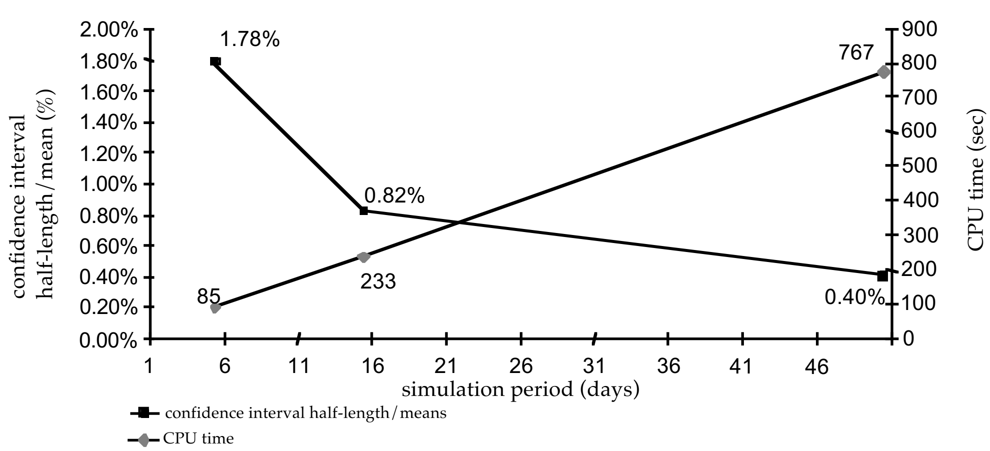

Figure 6. Confidence intervals and CPU time

put on the left y-axis, and of the required CPU time on the right y-axis. While the CPU time increases almost linearly with the simulation period, the development of the accuracy stresses the quadratic relation between the confidence interval length and the sample size.

For 60 generations with 20 individuals per generation, a relative half-length of 0.5% – as originally intended – leads to computation times of several days (cf. Figure 6). Due to product-related changes, long computation times are not acceptable in the planning process of such industrial applications, and planning engineers need the results almost "overnight." In this context, it may be necessary to obtain solutions in the optimization process based on shorter simulation periods. Of course, these solutions have to be handled with greater care since their validity is questionable. This approach is still reasonable, as "good" solutions of a simulation-based optimization might be tested in subsequent experiments using longer simulation periods.

Furthermore, a solution suggested by a simulation expert or computed by a metaheuristic controlled optimization may not be directly applicable to the underlying real-world BSDP. Here, further constraints such as budget restrictions, architectural and layout limits may bias the results. It should be kept in mind that the main purpose of the approach is to improve and simplify the manual search process of the planning engineers and not to necessarily find an individual that represents the optimal solution for the overall real-world problem.

4.2 Experiments – Part II

The aim of the experiments of the second part of the study is to compare the three metaheuristic-based approaches with the manual optimization. The results for the best solution found by the different approaches are shown in Figure 7.

In this figure, it can be seen that all three metaheuristics clearly improve the best manual solution, which defines the reference values (100%) for all three solution parameters under consideration. Furthermore, not only the best but also the average solutions found by the different heuristic approaches proved to surpass the manual procedure.

A significant reduction of the buffer sizes is achieved by all three approaches with SGA providing the best overall results. The cycle times can, as expected beforehand, be improved only to a small degree. Note that for the cycle times, an extension means an improvement. PGA finds a solution with the longest average cycle times, but obviously at the cost of a higher variance.

For all three solution procedures, the required CPU time depends almost entirely on the time to conduct the simulation experiments. In this respect, there are only marginal differences between the two simulation packages under consideration. As discussed above, a solution does only have one value for practitioners if it is found within a certain time limit. Therefore, the number of evaluated solutions per optimization process was restricted to 5000.

4.3 Experiments – Part III

The genetic algorithm-module SIMPLE/GA provides a variety of parameters to control the optimization process [33]. In the third series of experiments, the impact of some of these parameters is further analyzed. The significance of the influence of these parameters can be demonstrated by means of two experiments. In one series of runs, the parameter *Fitness Reference* was set to "*absolut*" and the option *Clone Best Solution* was selected to always choose the best solutions as a basis

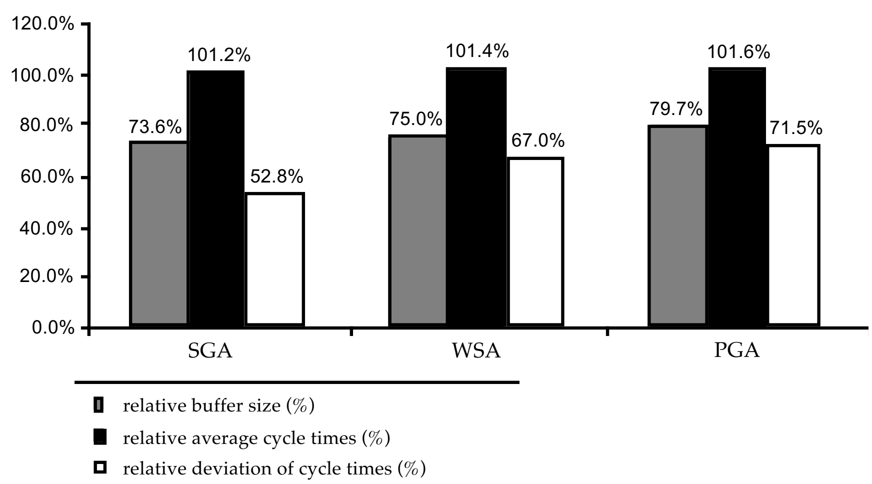

Figure 7. Relative buffer sizes, relative cycle time and relative deviation of cycle times compared to the best manual solution

for the next generation and to always copy the genes of the best solution without subjecting the latter one to crossover and mutation.

In another series, the *Fitness Reference* is set to "*relative*" and the option of cloning the best solution is not selected, following the more "classical" parameter settings for genetic algorithms. Figures 8 and 9 show the development of the fitness function for 60 generations of the best, worst and average individual, respectively.

The first parameter setting leads to an intensified search and a fast convergence of the best, the worst and the average fitness values within the population (cf. Figure 8), i.e., after about 15 generations only individuals with similar genes are combined with each other. The second parameter setting leads to a completely different behavior of the algorithm. Since the genes of the best solution(s) are not necessarily passed on to the next generation, there is not such a clear convergence of the algorithm. Based on the same initial population, the intensifying search leads to a lower (average) fitness value of the best solution of about 10%. However, it is not valid to conclude that this parameter setting generally leads to better results. The development of the fitness values also depends on other influences, e.g., the initial population, as some experiments indicate.

5. Conclusions and Further Research

In this paper, we have presented a simulation-based optimization approach for the body shop design problem. The approach is based on a combination of metaheuristics, such as genetic algorithms and simulated annealing, and simulation models of car body shops. The approach has been evaluated using a standard implementation of a simple genetic algorithm as well as commercial packages of both metaheuristics. To test and evaluate our approach, a comprehensive case study was undertaken at a German car manufacturer.

The presented results, along with the judgment of the planning engineers of the car manufacturer, allow the conclusion that simulation-based optimization is an excellent tool to support the optimization process within the conceptual design phase, which is usually conducted manually. Almost all results indicate that metaheuristics are able to detect solutions that the manually guided local search procedure has not dis-

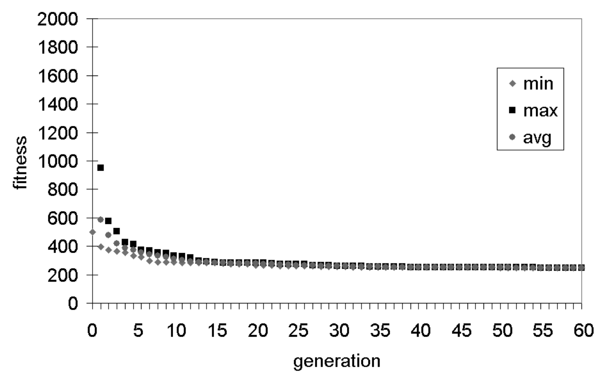

Figure 8. Fitness values over 60 generations with intensifying search

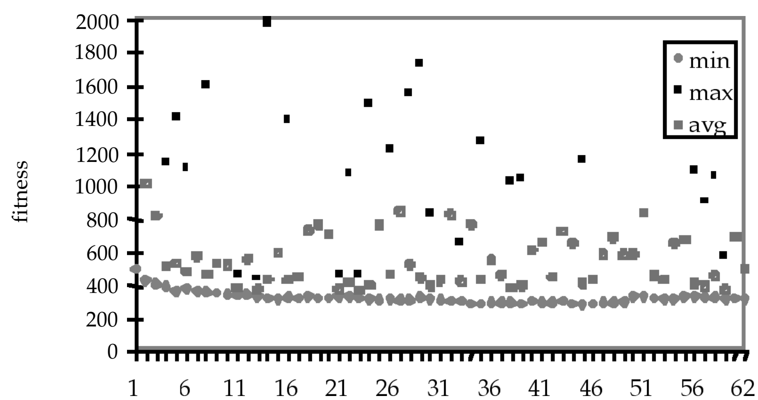

Figure 9. Fitness values over 60 generations with diversifying search

covered. The commercially available optimization tools turned out to provide a good solution quality.

Especially considering the availability of commercial optimization software, our approach allows a relatively easy adoption for other problem instances in this field by using the same objective function and optimization process. Here, the main problem lies in the calibration of the objective function presented, as the weights W_1, W_2 and W_3 have a significant impact on the overall solution quality.

The computation times turned out to be a problem if the solutions were to be estimated with the accuracy that is desirable from a theoretical point of view. Here, we have proposed an optimization process that neglects the demand for strong accuracy in the first phase. However, engineers need to be made attentive for the possible lack of validity of the suggested solutions.

Further research should concentrate on substituting simulation models by (analytical) queuing models of car body shops, since almost all of the computation time is needed to perform the simulation runs. Furthermore, the applied commercial optimization packages remain to be tested against more sophisticated metaheuristics, as e.g., tabu search [34], and optimization frameworks [35-36] than the simple implementation of the genetic algorithm.

The impact of the numerous parameters of the commercial tools on the optimization process needs to be evaluated on a broader basis, too. In this context, methods that support an automated adoption of parameters of the algorithm within the optimization process, e.g., the probabilities for crossover, the selection strategies or the computation of the fitness (relative or absolute), may be of great value for industrial applications [37].

To conclude, the approaches discussed have become an essential part of the planning process of the body shop engineers at BMW. Here, genetic algorithms will especially support the future planning processes of car body shops, as simulation has been for some years.

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