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MULTIOBJECTIVE SIMULATION OPTIMIZATION USING AN ENHANCED GENETIC ALGORITHM

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ABSTRACT

This paper presents an improved genetic algorithm approach, based on new ranking strategy, to conduct multiobjective optimization of simulation modeling problems. This approach integrates a simulation model with stochastic nondomination-based multiobjective optimization technique and genetic algorithms. New genetic operators are introduced to enhance the algorithm performance of finding Pareto optimal solutions and its efficiency in terms of computational effort. An elitism operator is employed to ensure the propagation of the Pareto optimal set, and a dynamic expansion operator to increase the population size. An importation operator is adapted to explore some new regions of the search space. Moreover, new concepts of stochastic and significant dominance are introduced to improve the definition of dominance in stochastic environments.

1 INTRODUCTION

Most real-world problems involve multiple conflicting objectives where improving one objective may deteriorate the performance in terms of one or more other objectives. Many heuristic search algorithms have been developed to solve multiobjective optimization problems including genetic algorithm (GA), simulated annealing, and tabu search. GA is a population-based search algorithm inspired by Darwinian evolutionary theory, survival of the fittest. It has been proven that GA is an intelligent optimization algorithm able to balance the tradeoff between exploration and exploitation. Other major advantages of GA for multiobjective optimization of simulation models include the following (Srinivas and Deb 1994):

- GA-based approaches are capable of finding a number of optimal solutions rather than a single solution (Deb 2001).
- GA-based approaches are capable of exploring the search space more thoroughly with the smaller number performance(s) evaluations than those based on local search, such as simulated annealing, and tabu search (April et al. 2003).
- GA-based approaches are less dependent on the good selection of the starting points, and they don't require neighborhood definition (April et al. 2003).

Traditional approaches for solving multiobjective optimization problems try to scalarize the multiple objectives into a single objective and change the problem formulation to a single objective optimization problem in which only a global optimal point is desired. However, there are some drawbacks to these traditional approaches which encourage the researchers and practitioners to use nondomination-based techniques to find a set of Pareto optimal points rather than just a single global optimal point (Silva and Biscaia 2003, Coello et al. 2002, Deb 2001, Srinivas and Deb 1994). The major drawbacks of traditional methods and motivations for using nondomination-based techniques include:

- The priority vector used in the scalarization process influences the final solutions.
- Alternative solutions will not be available to decisions makers without at least changing some parameters such as priority vector.
- Some optimal solutions may never be found if the objective function is not convex (real-life problems are seldom convex)
- There are implications in the homogenization of different performance measures, such as cost, quality of products, and cycle times, to a common unit of measure.

- Traditional approaches may not work effectively if objectives are noisy or have discontinuous variable space.

The purpose of this research is to develop a GA-based stochastic multiobjective optimization methodology to find Pareto optimal solutions for simulation models in a computationally efficient manner.

2 BACKGROUND

Our extensive review of the literature has revealed that only few attempts have been made in the area of multiobjective simulation optimization, most likely because of the existing uncertainties and complexities involved in the nature of the problems.

Mollaghasemi et al. (1991) proposed an approach in which they integrated the gradient search method and multiple attribute value function. Evans et al. (1991) reviewed some of the best-known multiobjective optimization techniques categorized based on the three types of approaches: prior, progressive, and posterior articulation preferences that can be used for optimization of simulation models.

Mollaghasemi and Evans (1994) introduced an interactive approach based on the previously known multiobjective optimization approach, called STEP method. Briefly stated, STEP method is a multiobjective programming algorithm which attempts to minimize the maximum deviation of objectives from the ideal solution using relative weight of deviations. A job shop model was used for application of the proposed interactive algorithm with six decision variables, the number of machines at each of six job stations, and four objectives including average time in system for three different part types and average machine utilization for all machine groups.

Teleb and Azadivar (1994) introduced an interactive approach by modifying the simple search method assuming objective functions and stochastic constraints are normally distributed. Boyle and Shin (1996) suggested an interactive approach, Pairwise Comparison Stochastic Cutting Plane (PCSCP), combining features from multiobjective mathematical programming and response surface methodology.

Baesler and Sepulveda (2000) suggested a new approach for multiobjective simulation optimization by integrating stochastic GA with goal programming method. This approach, unlike most previous approaches which disregard the stochastic nature of output responses, employs the variances of the responses in order to perform the search stochastically through the GA towards the solution with the minimum weighted deviations from the target levels. They used a statistical grouping procedure based on Tukey's method to cluster the individuals in a population that there is statistical difference between individuals of two different groups, but not between individuals within a group. The same authors applied their proposed methodology to design a cancer treatment center facility (Baesler and Sepulveda 2001). The four decision variables of the underlying system include number of treatment chairs at ambulatory treatment center, number of blood nurses, laboratory capacity, and pharmacy capacity. In this study, they considered four measures of system performance, including minimization of patient's waiting time and closing time and maximization of nurse utilization and chair utilization.

Joines et al. (2002) introduced a GA-based multiobjective simulation optimization approach by modifying the second version of nondomination sorting genetic algorithm (NSGA-II), proposed by Deb and Goel (2002). They applied their enhanced methodology for a real-world supply chain optimization problem with two objectives, namely, gross margin return on investment and customer service level. Applying the methodology, they found Pareto optimal solutions for different levels of customer service which provide a lot of information for the decision maker.

3 METHODOLOGY

This section presents the proposed methodology as a modeling framework for multiobjective simulation optimization problems. The proposed approach integrates discrete event simulation techniques, stochastic nondomination-based multiobjective optimization technique, and genetic algorithms. In this methodology, real coded GA is implemented to avoid difficulties of binary representation and plenty of bit operations, particularly when dealing with continuous search space with large dimension (Herrera 1998). Each individual solution is represented by a vector $\boldsymbol{x}=(x_1,x_2,\ldots,x_n)$, in which a decision variable x_i is represented by a real number within its lower limit a_i and upper limit b_i, i.e., $x_i \in [a_i, b_i]$ and the dimension of the vector is equal to the number of decision variables of the problem under study.

New operators are introduced to enhance algorithm performance of finding Pareto optimal solutions and its efficiency in terms of required computational effort. An elitism operator is implemented to ensure the propagation of the Pareto optimal set. An expansion operator, recently introduced by Shen and Daskin (2005), is employed to increase the population size of the GA up to the user-specified maximum population size if the number of Pareto optimal solutions in the current generation exceeds half of its population size. An importation operator is adapted to explore some new regions of the search space. Moreover, the new concept of stochastic domination is introduced to improve the definition of domination in noisy and stochastic environments.

The steps of the proposed algorithm are as follows:

1. Perform an initial experimentation in order to check the efficiency of using CRNs, estimate the initial population size, and possibly identify other parameter settings.

2. Create an initial population randomly or take user-specified individuals (or a combination of them).
3. Evaluate objective functions of the individuals and register all of them in the corresponding file.
4. Rank the population of individuals based on the new ranking strategy, and calculate their fitness values according to the new dummy fitness assignment.
5. Register stochastically nondominated individuals in the Pareto set file and update the file by discarding the dominated points.
6. Update the population size and implement elitism operation.
7. Employ importation operation to introduce a few new individuals randomly to the new population.
8. Select the pairs of individuals as parents in the reproduction operation using 2-tournament selection scheme based on their assigned dummy fitness.
9. Perform crossover and mutation operations to generate the offspring to fill in the remaining positions in the new population.
10. If the stopping criterion is met, terminate the search; otherwise, return to step 3.
11. Use the screening algorithm to reduce the obtained large set of Pareto optimal solutions to a manageable size.

Figure 1 depicts a flow diagram of this algorithm. A detailed description of each operation and step is provided in the following sections.

3.1 Initial Experimentation

The first step of the proposed methodology is to perform an initial experimentation to check the efficiency of using CRNs, estimate the initial population size and possibly identify other parameter settings. This initial experimentation helps the experimenter to check the applicability of the variance reduction technique as well as identify the appropriate parameter settings in order to enhance the performance of the algorithm and reduce the computational effort.

Employing CRNs is useful in reducing the variance when a positive correlation is induced among the design alternatives by putting them under similar experimental conditions. However, there are situations where using CRNs might induce a negative correlation among the design alternatives which can result in increased variance. The effectiveness of CRNs can be tested by running the simulation model with n replications for two different alternatives and checking whether or not the variance of their difference is less than the sum of their individual variances.

Goldberg et al. (1992) has found that when dealing with noisy and uncertain objective functions, a larger population size should be considered. This avoids premature convergence in a noisy and stochastic environment. Miller (1997) found that under certain assumptions there is a good approximation to estimate population size depending on the noise level.

3.2 Initialization

After estimating the initial population size, the initial population can be created by random sampling of each decision variable within its range of variation. The user can also include some promising solutions if he or she has prior knowledge about the problem under study. Another approach is to take initial solutions from either the boundary of the search space or scan the search space with equal intervals as a grid. An initial population can be generated by combination of the methods described above.

The evaluation of solutions in terms of the objective functions is accomplished by running the simulation model for a sufficient number of replications using a commercial simulation software package (for example, Arena Rockwell software). In this way, the simulation software estimates expected performance measures and their corresponding half-widths (or variances) for all solutions in the current population. The solutions with their corresponding objective functions values are all registered in a database to reduce computational time in subsequent generations.

3.3 Dominance in Simulation Context

In deterministic context, most multiobjective optimization applications are converging towards using the nondomination-based approaches because of the aforementioned problems in classical multiobjective methods. Let's assume that $f_i(A)$ and $f_i(B)$ are the values of objective function i $(i=1,\ldots,n)$ for two points A and B. Suppose that we want to minimize each objective function. It is defined that point A strictly dominates (is better than) point B if $f_i(A)$ is less than $f_i(B)$ for each i $(i=1,\ldots,n)$. Figure 2 illustrates the concept of strict dominance graphically for a manufacturing system with two performance measures in which we want to minimize both average monthly cost and average cycle time for a specific product. As it is shown in Figure 2, design A strictly dominates all designs in the shaded region.

The strict dominance definition must be modified for stochastic environments in which the objective functions don't take certain values and they are described with the expected values and variances. This uncertainty is typically resulting from randomness effect involved in the simulation modeling. Given the fact that in stochastic simulation models, we deal with noisy and random objective functions that are approximately normally distributed, we use different definitions to compare two points in the population. In such an environment, let's assume that $\overline{f}_i(\mathrm{A})$, σ_{A}^2 and $\overline{f}_i(\mathrm{B})$, $\sigma_{\mathbf{B}}^2$ are the expected values and variances of ob-

jective function *i* (i=1,...,n) for two points A and B, respectively.

Definition 1 *Point A stochastically dominates (is better than) point B if* $\overline{f}_i(\mathrm{A})$ *is less than* $\overline{f}_i(\mathrm{B})$ *for each i* (i=1,...,n).

In this case, because of the uncertainty involved in the objective function values, we are not sure whether or not Point A deterministically (or strictly) dominates (is better than) point B. As a result, we modify the strict dominance definition to stochastic dominance by taking the expected values of objective functions rather than certain values in deterministic context. However, in the stochastic environment we might be interested in knowing whether or not there is significant difference between the two points in our analysis.

Definition 2 *Point A significantly dominates (is better than) point B with a confidence level of (1-*α*)% if probability of* $\prod_{i=1}^{n} P(f_i(A) < f_i(B)) \geq 1-\alpha$, *where* α *is significance level (*$0 \leq \alpha \leq 1$*).*

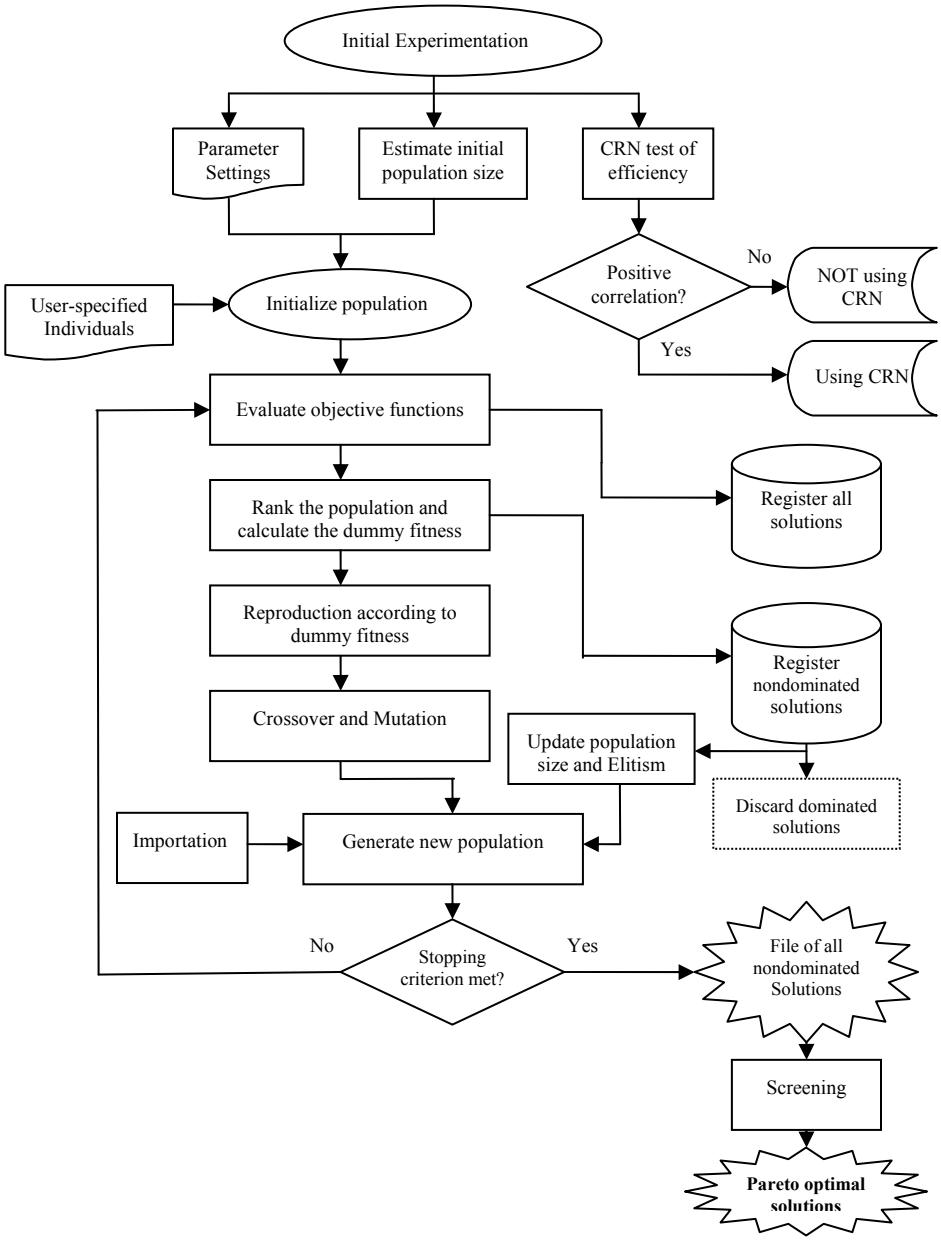

Figure 1: Flow Diagram of Methodology for Multiobjective Simulation Optimization

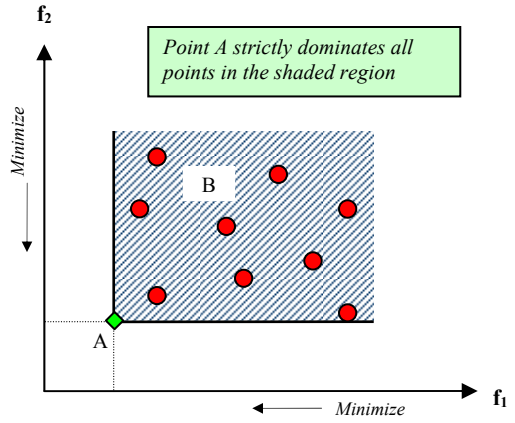

Figure 2: Illustration of Strict Dominance

Theorem 1 *If x and y are independent normal random variables with means* μ_x *and* μ_y *(*$\mu_x < \mu_y$*), and variances* σ_x^2 *and* σ_y^2*, the probability of P(x<y)=* $= 1 - Q(\frac{\mu_y - \mu_x}{\sqrt{\sigma_x^2 + \sigma_y^2}})$*, where the Gaussian error integral* $Q(x) = 1 - \Phi(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-t^2} dt$.

Proof If x and y are independent normal random variables with means μ_x and μ_y and variances σ_x^2 and σ_y^2, the probability of y is greater than x is calculated as $P(x < y) = P(0 < y - x)$. Assuming $\mu_x < \mu_y$, the change of variable $t = y - x$ results in $P(x < y) = P(0 < t)$, where t is a normal random variable with mean $\mu_t = \mu_y - \mu_x$ and variance $\sigma_t^2 = \sigma_x^2 + \sigma_y^2$ as shown in Figure 3.

Now, the probability of $P(x < y) = P(0 < t)$ is calculated as

$$P(0 < t) = Q(\frac{0 - \mu_t}{\sigma_t}) = Q(\frac{-(\mu_y - \mu_x)}{\sqrt{\sigma_x^2 + \sigma_y^2}}) = 1 - Q(\frac{\mu_y - \mu_x}{\sqrt{\sigma_x^2 + \sigma_y^2}}), \quad (1)$$

since $Q(-x)=1-Q(-x)$.

The integral described for $Q(x)$ does not have a closed-form expression, but an excellent closed-form approximation is suggested by Borjesson and Sundberg (1979) to estimate $Q(x)$ with an acceptable error.

The next section describes how this calculated probability can be employed to improve the concepts of the stochastic and significant dominance in the simulation context.

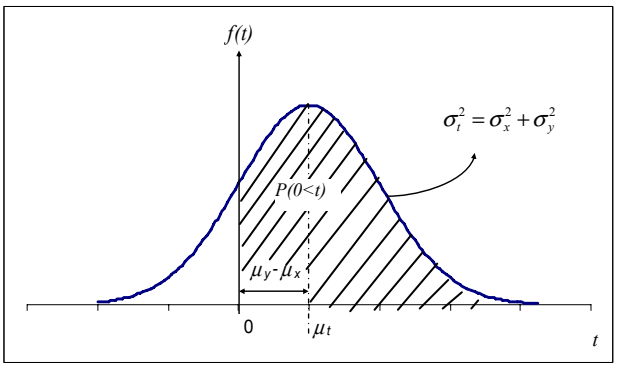

Figure 3: Plot of Normal Random Variable t

tion. Firstly, all stochastically nondominated individuals of the population are identified as the first category and assigned the dummy fitness value F_i of zero, which implies that there is no individual in the current population that is stochastically better than these identified individuals with respect to all objectives. The remaining individuals are stochastically dominated points which are compared to the nondominated points. Each stochastically dominated point in question is compared with the closest nondominated point to it (Figure 4). In this case, each stochastically dominated individual is assigned the dummy fitness equal to the product of superior probabilities between the dominated point in question B and the closest nondominated point A, that is, $\prod_{i=1}^{n} P(f_i(A) < f_i(B))$. This method of calculating the dummy fitness value has two advantages. First, given that the dominated points will eventually move towards the tradeoff curve, the dummy fitness assignments for the dominated points are calculated by comparing their position to their nearest point located in the tradeoff curve. Secondly, the dummy fitness assignment considers superior probability for stochastic environment giving more chance to be reproduced to the dominated point with higher variance, but with the same distance from the nondominated point.

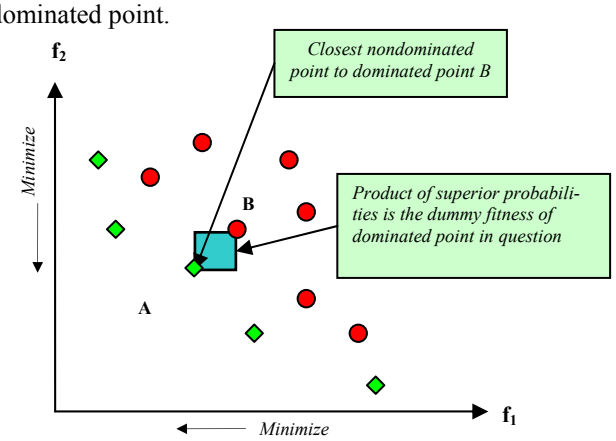

Figure 4: Illustration of Dummy Fitness Assignment for a Dominated Point

3.6 Crossover and Mutation

The pairs of selected parents in the reproduction process are submitted to the crossover and mutation operators to produce two offspring for the new population. The crossover operator exchanges the information between two parents with a pre-specified probability of occurrence p_c. A blended crossover operator (BLX-α), introduced by Eshelman et al. (1993), is performed in this algorithm. This operator starts by choosing randomly a number from the interval $[x_i-\alpha(y_i-x_i),\ y_i+\alpha(y_i-x_i)]$ where x_i, y_i are the ith parameter values of the parent solutions and $x_i < y_i$. To ensure the balance between exploitation and exploration of the search space, α=0.5 is selected. This operator is depicted in Figure 5, where a_i and b_i are lower and upper bounds of the decision variable, respectively.

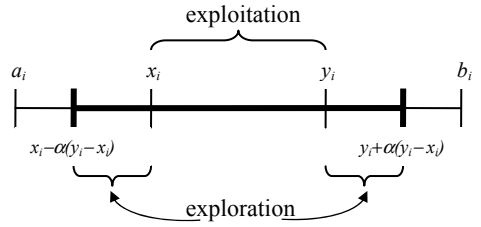

Figure 5: Blend Crossover Operator

After the crossover operation, the newly obtained solutions are exposed to mutation operation with a pre-specified probability of occurrence p_m. The non-uniform mutation operator, introduced by Michalewicz (1992), is employed. The new value of the parameter after mutation at generation t is given as

$$x_i' = \begin{cases} x_i + \Delta(t, b_i - x_i) & \text{if } \tau = 0 \\ x_i - \Delta(t, x_i - a_i) & \text{if } \tau = 1 \end{cases} \quad (2)$$

with τ being a random number which may have a value of zero or one, and

$$\Delta(t, y) = y\left(1 - r^{(1-t/g_{\max})^{\beta}}\right) \quad (3)$$

where r is a random number from the interval [0,1], g_{max} is the maximum number of generations, and β is a parameter chosen by the user, which determines the degree of dependency on the number of iterations. The interested reader is referred to the comprehensive paper written by Herrera (1998) for information on different variants of crossover and mutation operators for the RCGA.

3.7 New Population Generation

In order to enhance the algorithm performance and reduce the required computational time, a few genetic operators have been introduced to conduct the search process in the right direction. These genetic operators include elitism, expansion, importation, and crowded tournament selection. An elitism operator is implemented to ensure the propagation of the Pareto optimal individuals (best solutions) to the next generation. This is accomplished by copying all stochastically nondominated individuals in the current generation to the next generation. Because the number of nondominated solutions might become quite large, an expansion operator, recently introduced by Shen and Daskin (2005), is employed to increase the population size up to the user-specified maximum population size. In this case, if the number of Pareto optimal points in the current generation exceeds half of the current population size, the new population size is updated as twice the number of the nondominated individuals in order to create sufficient room for generating new individuals in the new population. If the updated population size exceeds the maximum population size, the crowded tournament selection operator (discussed in the next section) is activated to take the proportion of the nondominated individuals based on their diversity along the tradeoff curve. In this case, only half of the maximum population size is filled by nondominated individuals using the crowded tournament selection operator. In order to fill in the remaining room in the new generation, 80% of the remaining room is occupied by the offspring created via crossover and mutation operators and the other 20% are filled in by randomly generated new individuals using an importation operator (Shen and Daskin 2005). An importation operator is adapted to explore some new regions of the search space if they have possibly not been sampled yet.

3.8 Crowding Distance

In order to take the right proportion of nondominated solutions in the sense of maintaining a good spread of individuals along the tradeoff curve, a crowded tournament selection operator, originally introduced by Deb (2002) in NSGA-II, is employed. This new approach does not have the problems of using the sharing function method including appropriate selection of sharing parameter σ_{share} and the large computational complexity. Briefly explained, crowding distance estimates the density of the individuals surrounding a particular individual in the population. It is done by calculating the average distance of two points in either side of the point in question along each of the objectives. This measure, called the crowding distance, is used as an estimate of the perimeter of the cuboids formed by using the nearest neighbors as the vertices. Figure 6 shows how the crowding distance of an individual p is calculated

as the average side length of the cuboid. After all nondominated points in the population are assigned distance crowding values, individuals can be compared against one another. The distance tournament selection operator is performed to select the right subset of the nondominated set to copy to the next population. The interested reader is referred to Deb (2001) and Deb et al. (2002) for additional information.

3.9 Stopping Criterion

There are different approaches used to stop the sequence of successive population generations depending on the form of the response surface, the quality of desired optimal solution, and the assigned computational time. In this methodology, a stopping criterion is adopted based on the convergence speed towards Pareto optimal curve. If in the prespecified number of consecutive generations, no considerable improvement is found in the quality of the Pareto optimal curve, the algorithm is stopped. Alternatively, in the case of the assigned certain amount of computational time, the algorithm could be stopped after a specific number of generations. In this case, the Pareto optimal solutions found at the end of the search are used in the final step of the optimization process (screening Pareto set by clustering). It is important to note that a careful monitoring of the algorithm evolution is crucial to ensure that a sufficient number of generations is assigned for the successive convergence. The results obtained from the initial experimentation could provide good insight about the complexity of the underlying problem.

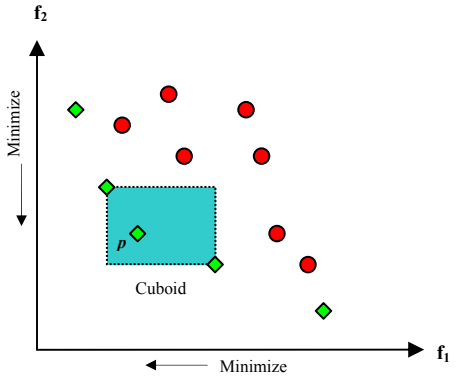

Figure 6: Illustration of Crowding Distance Calculation

3.10 Screening Pareto Set by Clustering

Since in most nondomination-based multiobjective problems the size of the Pareto optimal set becomes extremely large, some tools should be employed to prune it to manageable size for the decision maker. The literature review on cluster analysis reveals that there are several methods proposed for this purpose. For example, Morse (1980) provided a comprehensive review of different clustering methods including two general forms of direct and hierarchical clustering. The basic idea is to portray the nondominated set by a representative subset which reflects the characteristics of the main set without destroying any attributes of the obtained curve. In general, cluster analysis partitions a collection of N elements into P groups of relatively homogeneous elements, where $P < N$, selecting a representative individual for each of the P clusters.

In this methodology, an average linkage hierarchical clustering, introduced independently by several authors, is adopted to screen out the probably large Pareto optimal set obtained at the end of the search process. The mechanism is simple and the two clusters with minimum average distance are combined together into a larger cluster. This process continues until the desired number of clusters is gained. Then, the nearest solution to the centroid of each cluster is selected and the remainders are removed.

4 FUTURE WORK

Since this is an ongoing research effort, there are many aspects that have to be examined. First of all, in order to verify and validate the proposed algorithm, its performance and efficiency should be checked by applying it to a few test bed problems with different attributes and properties, including number and types of decision variables, decision variables' domains, number of objectives, discontinuity, multimodality, and noise level. Test bed problems could include a job shop model, introduced by Mollaghasemi and Evans (1994), with six integer decision variables and four objectives, and/or a flexible manufacturing system and a numerical example used by Teleb and Azadivar (1994). Then, the proposed algorithm should be benchmarked with a few state-of-the-art algorithms to prove its advantages and usefulness. These algorithms could be some of the methods found in the open literature of multiobjective simulation optimization (for example, see Avello et al. 2004, Baesler and Sepulveda 2000) or multiobjective evolutionary algorithms (see Deb 2001, Coello et al. 2002).

Since parameter settings of the genetic algorithms will strongly affect its performance and efficiency, appropriate selection of the algorithm parameters is highly desired. Although a good estimation of population size is given, appropriate options of other algorithm parameters including crossover and mutation rates and number of replications should be well investigated and helpfully suggested. It is worth mentioning that appropriate selection of these parameters strongly depends on the nature of the problem under study.

The algorithm is going to be applied to the real-world simulation problem of modeling the Space Shuttle flight hardware processes. The interested reader is referred to Mollaghasemi et al. (2000) and Cates et al. (2002) for additional information. This complicated problem consists of

more than 20 decision variables and two objectives of maximization of flight rate and safety.

Finally, user friendly software should be developed for the proposed algorithm so that many researchers and practitioners could take advantage of that. It is advisable that the developed software be compatible and capable of being integrated with most common commercial simulation software packages.

5 CONCLUSIONS

This paper presents an enhanced genetic algorithm approach for dealing with multiobjective simulation optimization problems. This approach integrates a simulation model with a stochastic nondomination-based multiobjective optimization method and genetic algorithms. New genetic operators have been introduced to enhance the algorithm performance in finding Pareto optimal solutions and its efficiency in terms of required computational effort as well as its robustness against noise. New concepts of stochastic and significant dominance employed in noisy environments could provide a more precise measure for better discrimination among competing design alternatives and handling uncertainty in simulation context.

Future research will focus on many aspects of this ongoing research. These include verification of the proposed algorithm by applying the approach to well-known test bed problems with different properties, and benchmarks with some of the state-of-the-art algorithms.

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