Proceedings of the 2015 Winter Simulation Conference
L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, eds.

A SIMULATION-OPTIMIZATION STRATEGY TO DEAL SIMULTANEOUSLY WITH TENS OF DECISION VARIABLES AND MULTIPLE PERFORMANCE MEASURES IN MANUFACTURING

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ABSTRACT

This work addresses the multiple criteria simulation optimization problem. Such a problem entails using an optimization strategy to manipulate the parameters of a simulation model to arrive at the best possible configurations in the presence of several performance measures in conflict. Pareto Efficiency conditions are used in an iterative framework based on experimental design and pairwise comparison. In particular, this work improves upon and replaces the use of Data Envelopment Analysis to determine the efficient frontier and replaces the use of a single-pass algorithm previously proposed by our research group. The results show a rapid convergence to a more precise characterization of the Pareto-efficient solutions. In addition, the capability of the method to deal with fifty decision variables simultaneously is demonstrated through a case study in the fine-tuning of a manufacturing line.

1 INTRODUCTION

The use of optimization is critical in manufacturing to approach three decision-making problems: design, control and improvement of processes and systems. The underlying optimization objective in all three can be casted as finding values for decision variables that most competitively meet several performance measures (PMs) or criteria simultaneously. Although the use of a single PM has been a popular approach to all three, decision models that involve multiple conflicting PMs simultaneously and explicitly more closely reflect manufacturing reality. These latter models fall in the realm of Multiple Criteria Optimization.

Nowadays, it is a prevailing practice to rely on computer simulation to estimate the performance of manufacturing processes and systems. Computer simulation is, obviously, a lot more convenient than carrying out experiments with actual systems. With ever-increasing computing power, this practice will only become stronger in the future. The concatenation of computer simulation and the optimization objective described previously has resulted in the field known as Simulation-Optimization. In a manufacturing context, Simulation Optimization is commonly applied to approach the decision-making problems of design, control or improvement of processes and systems. It follows then that –in this context- considering the simultaneous optimization of multiple criteria can contribute to make simulation-optimization closer to manufacturing reality. Therefore, it is of interest to study multiple criteria simulation optimization (MCSO) problems.

Incorporating the ability to deal with multiple criteria in conflict greatly enhances simulation-optimization. In order to fully exploit the power of a computer simulation model, however, it becomes

978-1-4673-9743-8/15/$31.00 ©2015 IEEE

paramount that simulation optimization methods be capable to help decide upon the values of tens of variables at a time in a convenient manner. The contribution of these variables should be assessed not only in their linear contribution to the PMs of interest, but also at least in their quadratic contribution and their second order interactions to be more useful for decision making. Indeed, nonlinearity and interaction are more rules than exceptions in manufacturing.

This work presents a MCSO strategy that is capable to incorporate tens of variables at a time and uses their linear, quadratic and second-order interactions to approach design, control and improvement of manufacturing processes and systems. The use of the strategy is demonstrated through the fine tuning of a theoretical simulated manufacturing line with 50 decision variables and 2 PMs in conflict.

2 BACKGROUND

The path to the MCSO strategy shown in this manuscript can be traced back to a series of manufacturing papers of our research group that have built upon each other as detailed next. The first idea related to manufacturing simulation-optimization in our group is presented in (Cabrera-Ríos, Mount-Campbell, and Irani 2002a), where the design of a manufacturing cell was approached through discrete-event stochastic simulation and the maximization of profit as the sole PM. The optimization task was not iterative, thus the strategy in this work can be classified as a single-pass, single criterion, simulation optimization one.

The second relevant work is (Cabrera-Ríos et al. 2002c), where design and process variables were included to meet multiple criteria modeled as a single composite objective function in the context of reactive polymer processing. The simulation type in this case relied on finite-element techniques, so it was continuous and deterministic in nature. Again the strategy was single-pass, single-criterion, simulation optimization.

The next step was to include multiple PMs in parallel. Using continuous physics-based simulation, this progress was documented in (Cabrera-Ríos, Castro, and Mount-Campbell 2002b; Castro et al. 2003; Cabrera-Ríos, Castro, and Mount-Campbell 2004; Castro, Cabrera-Ríos, and Mount-Campbell 2004; Castro et al. 2005). The cases under study were in the context of polymer processing ranging from in-mold coating, to compression molding and injection molding. In these cases, the strategy was single-pass, multiple criteria, simulation optimization. An additional characteristic in these works was the use of Data Envelopment Analysis (DEA) to solve the associated multiple criteria optimization problem. The DEA model adopted for such means was based on linear optimization and could detect all solutions that were in the convex part of the Pareto-efficient frontier of the problem; however, solutions that were in the non-convex part escaped it. It was, thus, deemed necessary to find an effective way to detect all solutions, those in the convex and in the nonconvex parts of the efficient frontier.

The possibility to detect the entire set of solutions belonging to the efficient frontier came along in the shape of a full pairwise comparison scheme reported in (Rodríguez-Yañez, Méndez-Vázquez, and Cabrera-Ríos 2014) where an injection molding process improvement was approached in a single-pass, multiple criteria, simulation optimization strategy.

In (Villarreal-Marroquín, Cabrera-Ríos, and Castro 2011; Villarreal-Marroquín et al. 2013), the first iterative simulation-optimization schemes in our group were reported for polymer injection molding (continuous simulation) and control/improvement of a painting line for automotive parts (discrete event simulation), respectively. These were iterative, single-criterion, simulation optimization schemes. An iterative algorithm capable to deal with multiple criteria using DEA was subsequently developed and reported in (Villarreal-Marroquín, Cabrera-Ríos, and Castro 2011). This is, then, an iterative, multiple criteria, simulation optimization scheme.

The present work introduces an iterative MCSO strategy capable to detect both the convex and nonconvex parts of the efficient frontier through the adoption of the scheme reported in (Rodríguez-Yañez, Méndez-Vázquez, and Cabrera-Ríos 2014), so it improves and replaces the use of DEA. It also incorporates the possibility of analyzing tens of variables through an economic experimental design proposed by (Méndez-Vázquez et al. 2014a) which ensures the possibility of estimating full quadratic regression models, that is, regression models that include linear, quadratic and second-order interaction terms. A collection of experimental designs with these capabilities was described in (Méndez-Vázquez et al. 2014b) and can be found online in:

http://yaileenmendez.wix.com/experimentaldesignlv

3 LITERATURE REVIEW

Simulation optimization has been an active area. Several strategies can be found in the literature as reviewed by (Carson and Maria 1997, Fu 2015). It is evident, however, that the vast majority has focused on the use of a single criterion optimization. Regarding multiple criteria simulation optimization, a recent review by (Andradóttir 2015) evidences how Genetic Algorithms (GA) have become a popular to approach problems of this nature, as exemplified by (Al-Aomar 2002; Ding, Benyoucef, and Xie 2003; Lin, Sir, and Pasupathy 2013). GAs is heuristic in nature, thus optimality cannot be guaranteed as a result. It is then understandable, then, that optimality certainty be a worthy objective. The work of (Mollaghasemi and Evans 1994), falls into the category of iterative multiple criteria optimization, although their approach favors the definition of a preference structure among PMs a priori, which departs from the non-parametric point of view advocated in this work. The works of (Zakerifar, Biles, and Evans 2011; Couckuyt, Deschrijver, and Dhaene 2012; Dellino, Kleijnen, and Meloni 2012) approach multiple criteria simulation optimization models using Kriging models with various degrees of success, adding evidence to the soundness of using metamodeling strategies to support the determination of competitive solutions in the presence of conflicting PMs. Indeed, there seems to be interest in the assessment of multiple criteria using simulation in different production applications such as planning and scheduling (Duvivier et al. 2007), inventory management (Mortazavi and Arshadi khamseh 2014), as well as scientific endeavors such as the analysis of intermolecular interaction (Stöbener et al. 2014). The present work adds to this body of literature by adding capability in iteratively dealing with tens of variables at a time, aided by saturated second-order regression models, using a Pareto-efficiency scheme of exact nature to approach multicriteria simulation optimization problems.

4 PROPOSED METHOD

The proposed strategy integrates the use of experimental design, simulation and metamodelling techniques to solve multicriteria optimization problems. In Figure 1 schematically shown the proposed method which is described below.

The method starts with an experimental design (DOE) from which a simulation is performed at each design point (1-2) and an initial incumbent solution is obtained (3). The incumbent solution here corresponds to the Pareto-efficient frontier that represents the set of best compromises between all performance measures in the experiment. With the simulated experiment, one metamodel per performance measure is obtained (4) and used to make predictions in the discretized experimental region (5). Using the Pareto analysis, potentially Pareto efficient points are detected (6-8). These predicted points are then simulated and joined with the incumbent solution to determine if a new Pareto efficient frontier has been found (9). If the Pareto-efficient frontier does not change, then the incumbent solution is reported and no more iterations are performed. Otherwise the incumbent solution is updated and the newly-simulated points are added to the set available points and a new iteration begins with the constructions of new metamodels (4). In detailed fashion, the method is as follows:

Initialization

- Set k = 0
- Initial DOE: Run a first design of experiments D_0 with n simulation runs considering all variables (L variables) and all objectives (J Criteria), where D stands for Design. Each controllable variable and performance measure must be scaled to fall between -1 and 1 to avoid dimensionality problems.
- Select incumbent: Analyze D_0 to determine which of its points are Pareto Efficient. I_0 now contains the Pareto Efficient points of D_0. I stands for incumbent.

  A Pareto efficient solution will be found when, in the full pairwise comparison with the rest of the solutions, there is no other solution that dominates it in all PMs simultaneously.

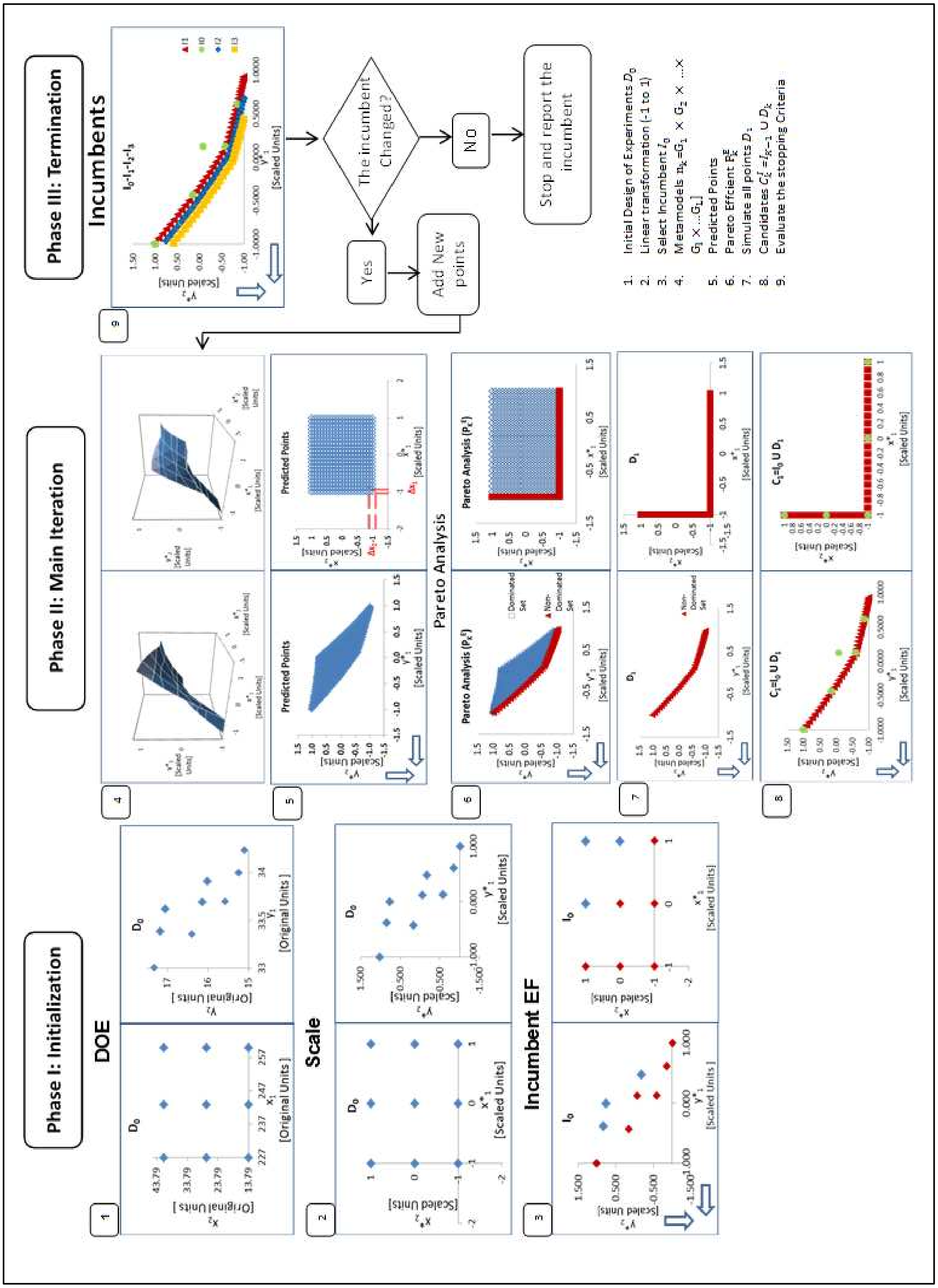
- Set $D_0^{available} = D_0$

Main Iteration

- Update counter k= k+1
- Use $D_{k-1}^{available}$ to fit all J metamodels, y_j [k].
- Use metamodels to predict the values of all J objective functions using a grid of $\mathrm{n_k}$= [$\mathrm{G_1} \times \mathrm{G_2} \times \ldots \times \mathrm{G_l} \times \ldots \mathrm{G_L}$] points, where $\mathrm{G_l}$ is the number of equidistant discrete points for the $\mathrm{l^{th}}$variable. Store these points in a matrix $\mathrm{P_k}$ with dimensions [$\mathrm{n_k} \times$ (L+J)], where P stands for predicted
- Analyze $\mathrm{P_k}$ to determine which of its points are Pareto Efficient. Store the efficient points in $\mathrm{P_k^E}$(where P stands for predicted and E stands for Efficient).
- Simulate all points in $\mathrm{P_k^E}$. Store the simulated results in a matrix D_k.
- Set $C_k^I = I_{K-1} \cup D_k$, where C stands for candidates and I for incumbent.
- Analyze $\mathrm{C_k^I}$ to determine which of the points are Pareto Efficient. Store the efficient points in $\mathrm{I_k}$.

Termination

- Evaluate the stopping Criteria. If $\mathrm{I_k} = \mathrm{I_{k-1}}$, then terminate the algorithm and present the incumbent solution $\mathrm{I_k}$. Otherwise, update $\mathrm{D_k^{available}} = \mathrm{D_{k-1}} \cup \mathrm{D_k}$ and reiterate.


Phase I: Initialization
DOE
Scale
Incumbent EF
Phase II: Main Iteration
Pareto Analysis
Predicted Points
Pareto Analysis (P_k^E)
Phase III: Termination
Incumbents
The incumbent Changed?
Yes
Add New points
NO
Stop and report the incumbent
1. Initial Design of Experiments D_0
2. Linear transformation (-1 to 1)
3. Select Incumbent I_0
4. Metamodels n_k = $G_1 \times G_2 \times \ldots \times G_1 \times \ldots G_L$]
5. Predicted Points
6. Pareto Effcient P_k^E
7. Simulate all points D_1
8. Candidates $C_k^I = I_{K-1} \cup D_k$
9. Evaluate the stopping Criteria

5 CASE STUDY: PRODUCTION LINE WITH 50 WORKSTATIONS

This section illustrates how a multicriteria optimization problem of 50 variables and 2 PMs is approached with the proposed method. Consider a fictitious production line with 50 workstations in series simulated with the software package Simio (Joines and Roberts 2013; Kelton, Smith, and Sturrock 2013), as is illustrated in Figure 2. The simulation is run for 8 hours per day with 10 replicates. The simulation model have an interarrival entity time that follows an exponential distribution with a mean equal to 3 minutes. The simulation parameters of interest were the mean process time on each of the workstations (WS_i). The process time of each workstation was assumed to follow a normal distribution with a mean that varied in three levels and a constant standard deviation of 0.25 minutes. Figure 3 shows the ranges of values to be explored for the process time of each workstation. It is further assumed that the nominal process time can be chosen by a particular user, so the problem at hand involves deciding upon the nominal process time for each of the fifty workstations. This theoretical problem was presented in (Méndez-Vázquez et al. 2014a), where it was treated with the iterative single criterion simulation optimization described in (Villarreal-Marroquín et al. 2013).

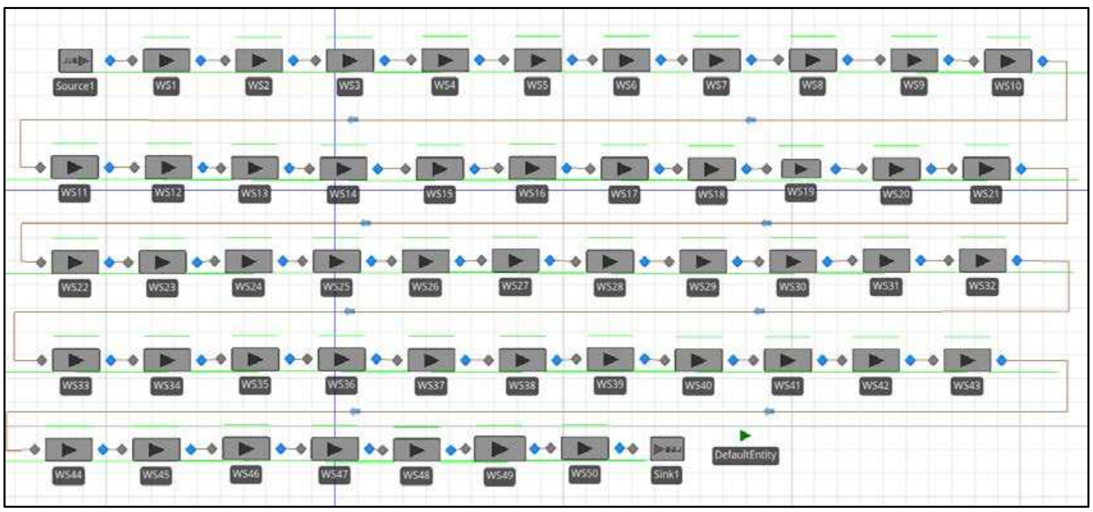


Figure 2: Simulation model for a production line with 50 workstations.

The PMs of interest were the system time (F_1) defined as the period of time elapsed since a raw part to be processed enters the system until it exits as a finished product, and the average utilization of all workstations (F_2). The first one is to be minimized while the second one is to be maximized.

The proposed method begins with the initialization phase where an initial experimental design (D_0) is simulated using the simulation model described previously. The experimental design used for this case is a D-optimal design generated using the statistical software JMP. The experimental design in this case is for 50 variables at three levels each, and has 1327 runs. The number of runs corresponds to the minimum number of necessary runs to estimate a second order model, as proposed in (Méndez-Vázquez et al. 2014a).

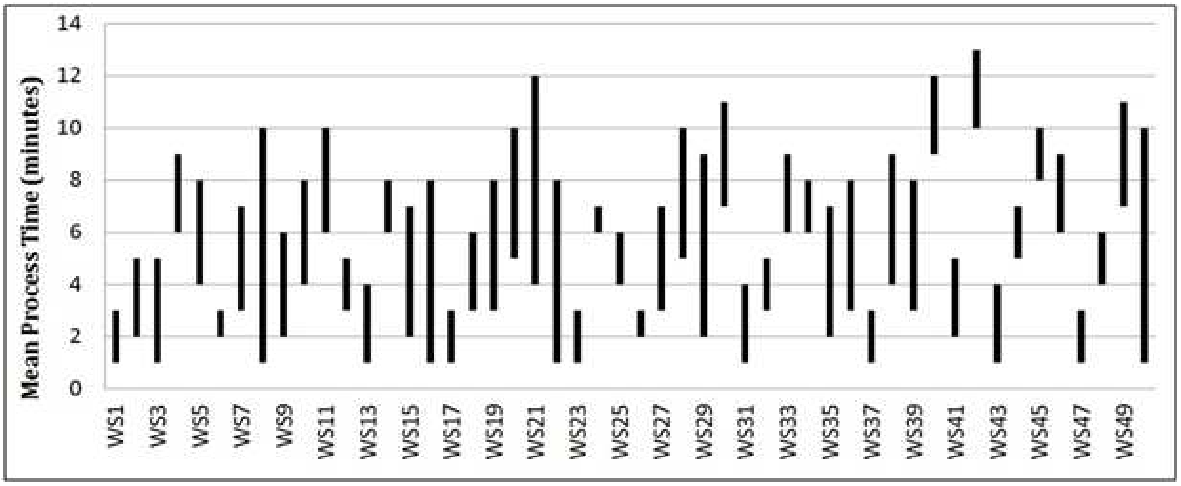


Figure 3: Range of values for the workstations' mean process time in simulation model.

The natural variables and the simulated values of the PMs are coded using a linear transformation to make them fall in the range of [-1,1] to avoid dimensionality problems. With these coded values the efficient frontier was found, using a MATLAB code available in our group to carry out the full pairwise comparison (Camacho-Cáceres et al. 2015). The found efficient frontier represents the initial incumbent solution (I_0) as shown in Figure 4. Do notice that, for representation purposes, both PMs are shown as minimization cases. Indeed, any maximization case can be turned into an equivalent minimization cases through a suitable linear transformation.

With I_0 at hand, the iterative phase of the algorithm begins. To generate predictions within the experimental region one second order regression metamodel per PM was constructed using D_0. Each metamodel consisted of 1326 terms. A discretization of the experimental region was performed with an increment of 0.25 units in the natural values and sampled using 30,000 uniformly distributed data points.

Predictions were then obtained, using the metamodels, in these 30,000 points for both PMs. In turn, these predicted solutions were evaluated to determine the Pareto-efficient ones. Do notices that the number of Pareto Efficient Solutions is expected to be considerably less than the original number of solutions under analysis. The Pareto Efficient Solutions at this point are predictions so an actual simulation must be carried out at these attractive points. With these new points, the incumbent solution I_0 must be revised for Pareto-efficiency. When the comparison was carried out, 3 new points added to the efficient frontier and 6 points of the incumbent solution I_0 were now dominated points. Consequently, these dominated solutions were deleted from the new incumbent solution I_1 (Figure 5).The points of the candidate set D_1 are added to the available points D_0, and the second iteration of the algorithm ensued.

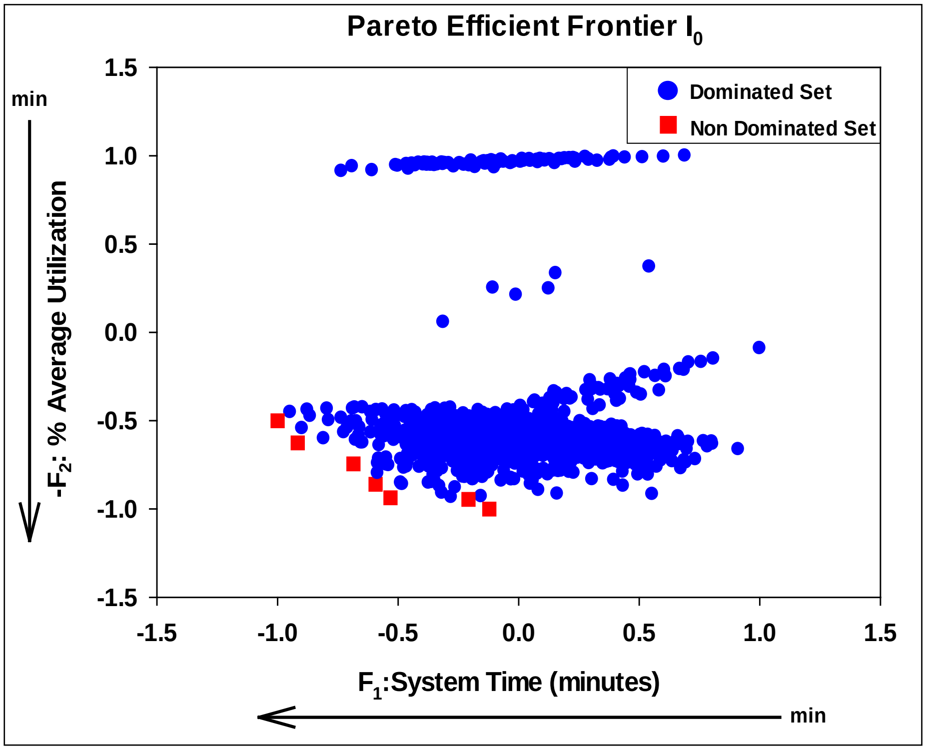


Figure 4: Initial pairwise comparison considering both objective functions for case of 50 variables.

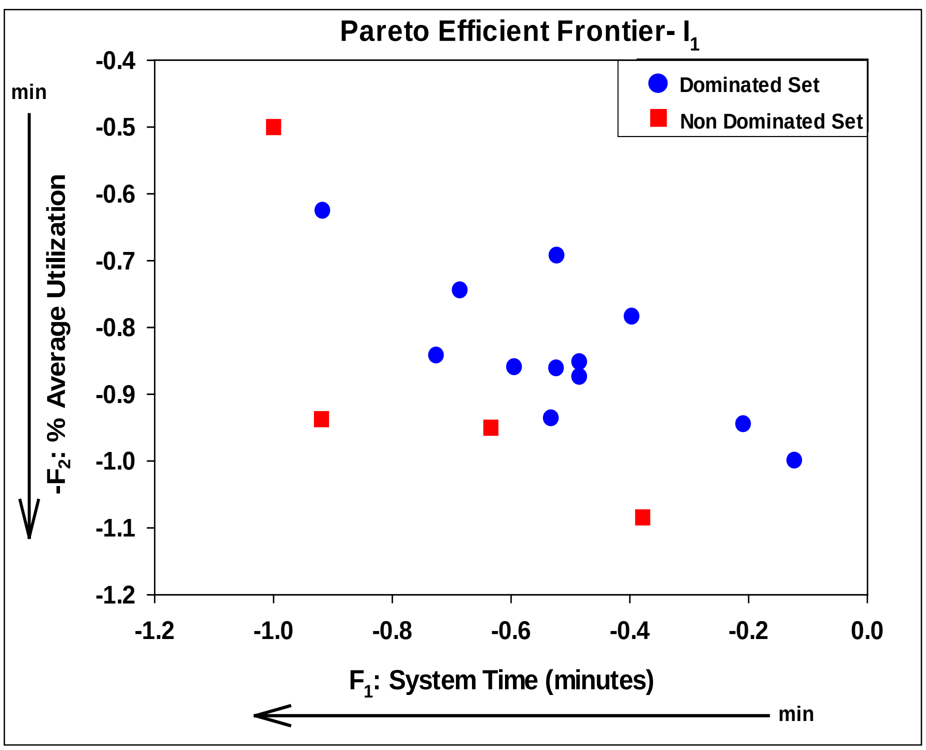


Figure 5: Pairwise comparison between I_0 and D_1 considering both objective functions.

The second iteration follows the same structure as before, with the creation of a new set of potential solutions D_2. These combinations were then simulated and compared with the incumbent solution I_1 using Pareto conditions (Figure 6). A new point is added to the efficient frontier to obtain a new efficient frontier (I_2). The candidate set of solutions D_2 were then added to the available points to calculate the new metamodels in a new iteration.

One more iteration was necessary to bring the method to a stop. It must be recalled at this point that the method stops only when no modifications are introduced in the current efficient frontier. The solutions for the initialization and each of the iterations are shown in Figure 7. The five solutions identified by the method represent the best possible tradeoffs between cycle time and average machine utilization. Each of these five solutions contain the prescriptive values at which each of the 50 workstations must be set.

When looking into the progression of the method in its two PMs (Figure 7), it can be appreciated how the method effectively explored beyond the initial experimental (simulation) samples. It is also clear that the efficient frontier would benefit from a finer exploration in that zone. This is left for future work, where a progressive refinement of the sampling increments in the so-called grid of the main iteration of the method will be investigated.

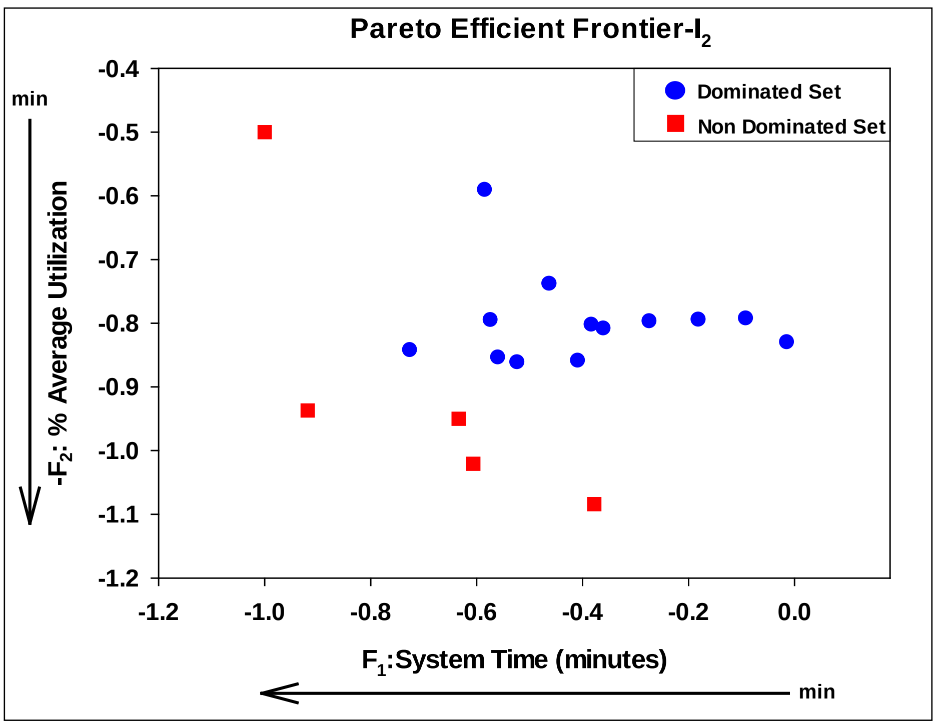


Figure 6: Pairwise comparison between I_1 and D_2 considering both objective functions.

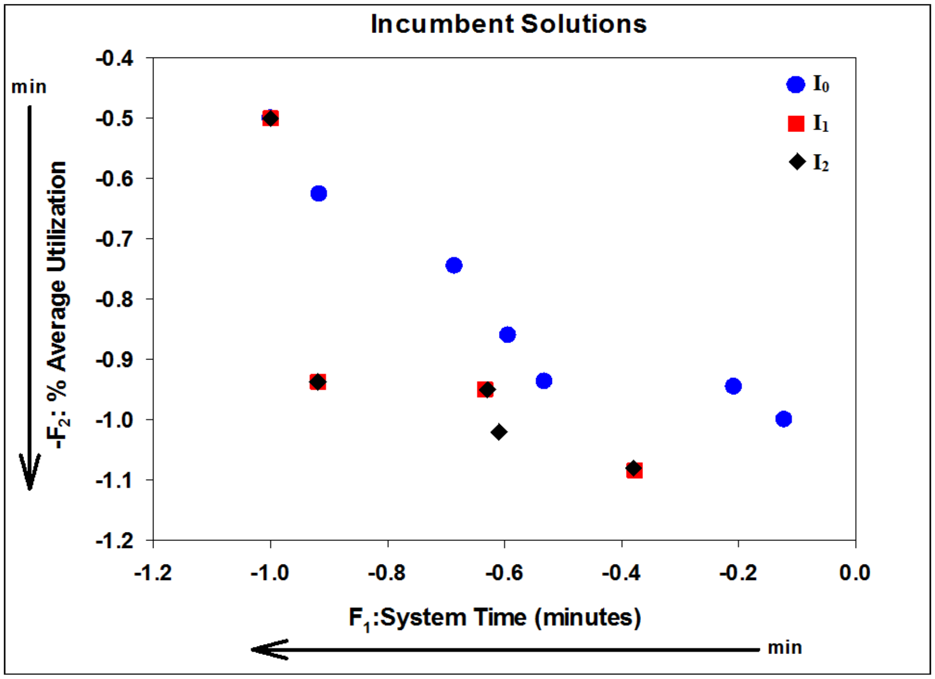


Figure 7: Each of the incumbent frontiers (I_0-I_2) of the problem under study.

6 CONCLUSIONS AND FUTURE WORK

This paper presents an iterative multiple criteria simulation optimization strategy capable to handle tens of variables at a time. In its current state, the method is an improvement over single-pass methods as well as the use of Data Envelopment Analysis models as previously proposed by our group. Manufacturing decisions regarding design, control and improvement of processes and systems can greatly benefit from using the proposed optimization strategy from the point of view of its capabilities -multicriteria, multifactorial- as well as its frugality in terms of the number of simulation runs. Future work includes assessing the method's runtime as relevant information for those cases where decision times are short.

ACKNOWLEDGMENTS

This material is based upon work supported by the National Science Foundation (NSF) under Grant HRD 0833112 (CREST program), as well as the National Institutes of Health (NIH) MARC Grant 5T36GM095335-02 ‘Bioinformatics Programs at Minority Institutions’. The coding work of MS Katia Camacho-Cáceres is also gratefully acknowledged.

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