A Review of Evolutionary Multiobjective Optimization Applications in the Area of Production Research

Christos Dimopoulos
Department of Computer Science and Engineering
Cyprus College
P.O Box 22006, 1516 Nicosia, Cyprus
Email: dimopoulos@cycollege.ac.cy

***Abstract*- Evolutionary computation methods have been used extensively in the past for the solution of manufacturing optimization problems. This paper examines the impact of the fast-growing evolutionary multiobjective optimization field in this area of research. A considerable number of significant applications are reported for a wide range of relevant optimization problems. The review of these applications leads to a number of conclusions and establishes directions for future research.**

I. Introduction

The effectiveness of evolutionary computation methodologies in the solution of multi-objective optimization problems has generated significant research interest in recent years. A number of evolutionary multiobjective optimization (EMO) methodologies have been developed and are being continuously improved in order to achieve better performance. These techniques have illustrated their competency against traditional multiobjective optimization techniques in the solution of this type of problems and are now considered to be a robust optimization tool in the hands of researchers and practitioners. An excellent introduction to the concepts of multiobjective optimization as well as a review of EMO techniques can be found in [1].

While initial applications of EMO techniques focused on typical benchmark optimization problems, an increasing number of researchers are now addressing problems related to real-life optimization. One optimization area of particular business interest is the area of production research. Evolutionary computation methods have illustrated their efficiency in handling a wide range of difficult NP-hard optimization problems associated with this area of research. A comprehensive review of relevant applications can be found in [2].

The aim of this paper is to review the state of the art in EMO applications for the solution of multiobjective manufacturing optimization problems. A summary of the most significant approaches is provided for major areas of production research such as scheduling (section 2), production planning and control (section 3), cellular manufacturing (section 4), flexible manufacturing systems (section 5) and assembly-line optimization (section 6). Section 7 analyses the findings of this review and proposes direction for future research.

II. Scheduling

Single-objective scheduling optimization problems have traditionally attracted considerable research interest from evolutionary computation researchers, since the encoding of solutions is straightforward and a number of well-tested recombination operators enhance the robustness of the optimization process [2]. While EMO research in the same area has not been as fruitful, a number of efficient optimization methodologies have been proposed during the last decade. These approaches are discussed in the following paragraphs:

A. Flowshop Scheduling

Murata & Ischibuchi [3] were among the first researchers to propose an EMO algorithm for the solution of flowshop scheduling problems. Their algorithm adopted an aggregating weighted-sum approach for the concurrent optimization of objectives. The value of the objective weights did not remain constant throughout the process but was instead selected randomly each time a crossover step needed to be executed during the evolutionary process. In that way the optimization search followed various directions within the same optimization run. The algorithm kept track of the non-dominated solutions discovered during the optimization process. A number of these solutions were fed back to the process thus incorporating the concept of elitism into the algorithm. The proposed approach performed favorably to Schaffer's VEGA [4] algorithm and to a fixed-weight evolutionary algorithm when applied to a flowshop scheduling problem with the aim of simultaneously minimizing the makespan and the tardiness of jobs. The same authors also suggested an extension to the algorithm by incorporating a local search process to all individual solutions produced during each generation [5]. This search process was later refined and optimized by Ischibuchi and Yoshida [6]. Ischibuchi and Yoshida also proposed the integration of the suggested local search technique with alternative evolutionary multiobjective algorithms such as NSGA-II [7] and SPEA [8]. Their experimentation showed that the hybridized version of the multiobjective optimization algorithms produced favorable results in comparison to the stand-alone version.

Shridar and Rajendran [9] considered a similar scheduling problem in a flowline-based cellular manufacturing system. They proposed an algorithm that maintained two subpopulations of solutions initialized with the help of heuristic procedures. Each subpopulation focused on the minimization of makespan and total flow time of jobs respectively. Multiobjective optimization was achieved through a specially designed operator (DELTA) that compared chromosomes in terms of all objectives considered. Weights were assigned to individual objectives for preference purposes. The algorithm produced a single job sequence that was further optimized through adjusted pairwise interchanges to produce a single optimal schedule. The effectiveness of the proposed algorithm was tested against a number of heuristic processes on various benchmark problems.

Sikora [10] addressed the problem of simultaneous lot sizing and sequencing within the context of a capacitated flow line. He presented an evolutionary algorithm that facilitated the concurrent solution of both problems using a linear combination (without weights) of three objectives as the driving force of the optimization process: minimization of makespan, overtime and holding costs. While the article discussed in detail the conflicting nature of the objectives considered, neither a weighted-aggregating, nor a Pareto-based ranking evolutionary approach was proposed as an optimization methodology.

Onwubolu and Mutingi [11] approached the flowshop scheduling problem considering the minimization of total tardiness and the minimization of the total number of tardy jobs as the optimization objectives. Each objective was initially considered independently and individual near-optimal values were found. The simultaneous optimization of both objectives was accommodated through a simple technique that identified strings with the same genotype evolved by both populations. These strings were regarded by the authors as good compromise solutions for the optimization problem considered.

Recently, Bagchi [12] has illustrated the use of an enhanced NSGA algorithm [13] for the solution of flowshop, job-shop and open-shop scheduling problems. He proposed the use of the 'Design of Experiments' methodology for the optimal parameterization of the proposed algorithm and he incorporated the concept of elitism within the structure of the original NSGA algorithm. The objectives considered where the minimization of makespan, total flow time, and tardiness of all jobs in the system. The usefulness of the proposed methodology was illustrated on a number of test problems taken from the literature.

B. Job-Shop Scheduling

Mesghouni et al. [14] considered the typical job-shop scheduling problem with the primary objective of minimizing the makespan of all jobs to be processed. The solution methodology consisted of a Constrained Logic Programming algorithm that provided initial solutions for the evolutionary optimization process. Multicriteria analysis followed the identification of a set of solutions that satisfied the objective of minimum makespan. The PROMETHEE multicriteria analysis technique was employed for the identification of non-dominated solutions based on the minimization of makespan, minimization of the standard deviation of the workload of the resource, minimization of the mean completion time and the minimization of the standard deviation of completion time. The end-user was responsible for choosing among the alternative solutions generated and changing the objective weights according to his/her preferences.

An interesting study on the solution of the job-shop scheduling problem using evolutionary computation algorithms was presented by Esquivel et al. [15]. They showed that using the concepts of multi-recombination (production of multiple offspring by the same pair of parents during crossover and choice of the best one) and incest prevention (recombination restricted only to individuals without common ancestors) evolutionary computation algorithms produce better results both in the single and multiobjective instances of the problem. For the multiobjective case they proposed both a subpopulation-based approach, where each subpopulation optimized a separate objective and the combined population optimized an aggregated combination of the objectives considered, and a Pareto-ranking based approach utilizing the concept of elitism. Encouraging results were reported for both approaches; however, no comparison with alternative multiobjective optimization techniques was attempted.

C. Case Studies

A number of researchers have illustrated how the principles of EMO can be used for the solution of practical multiobjective optimization problems in the area of scheduling. Shaw & Fleming [16] considered a practical scheduling problem for a company that produces chilled ready mills. The MOGA evolutionary multiobjective optimization technique [17] was proposed for the simultaneous minimization of omissions, lateness and shift ends. A comparison of the proposed algorithm with a typical weighted sum approach illustrated its ability to provide a wealth of potential solutions while maintaining its optimization ability.

Tamaki et al. [18] presented a case study on the application of a multiobjective evolutionary computation methodology for the solution of a scheduling problem in a plastics forming plant. The problem was modeled as an unrelated parallel machines scheduling problem. A typical Pareto-based ranking technique with elitism was used during the evolutionary process with the objective of simultaneously minimizing the sum of idle time of every machine, the maximum tardiness of jobs and the makespan of jobs. A typical example of the algorithm's application was provided.

Finally, Khoo et al. [19] illustrated how a generic practical scheduler for a manufacturing production system can be built. Their proposed scheduler consisted of a database that provided scheduling data, an evolutionary optimizer that generated near-optimal schedules, and a schedule-builder that was responsible for the transformation of any evolved sequence into a legal schedule. The scheduler was capable of handling various types of scheduling problems (job-shop, flow-shop, cellular manufacturing) with various types of objectives and constraints. The scheduler also provided a user interface with front-end analysis capabilities. One of the features of the proposed scheduler was its ability to handle multiple objectives. However, optimization was not achieved in the typical Pareto-ranking fashion. A schedule was initially generated that was optimal with regards to the makespan objective. The schedule builder was responsible for transforming this schedule in order to simultaneously minimize the tardiness objective.

III. Production Planning And Control

Production planning and control lies at the heart of the manufacturing process. Irrespective of the production planning and control system used (push, pull, agile manufacturing), a number of difficult optimization problems arise that cannot be efficiently solved through traditional optimization techniques. Evolutionary computation methodologies as well as alternative metaheuristic algorithms have been employed for this purpose [2]. Recently, a number of researchers have applied the evolutionary computation principles in an attempt to approach multiobjective optimization problems in the area of production planning and control. Significant applications are discussed in the following paragraphs:

Li and Man [20] discussed the multiobjective earliness/tardiness scheduling and planning problem in the context of a manufacturing system. An elaborate mathematical model of the problem was presented with the aim of simultaneously minimizing the number of unbalancing processes, the cost of early production penalties and the cost of tardy production penalties. A Pareto ranking based evolutionary multiobjective optimization technique was employed for the solution of the problem, however, no implementation information was provided in detail. An illustrated example depicted the validity of the proposed approach.

The optimal process plan selection problem was addressed by Awadh et al. [21] and Zhou and Gen [22]. In both cases evolutionary computation algorithms were proposed for the solution of the single objective version of the problem. However, since this problem can be formulated as a shortest path network problem, a number of well-known analytic algorithms exist for its solution. The authors proposed extended versions of their algorithms that explicitly considered the multiobjective version of the problem, based on the minimization of cost and maximization of quality of the production plans. Awadh et al. employed an aggregating weighted sum optimization approach, while Zhou and Gen preferred the adaptive objective evaluation hyperplane technique. A limited number of comparative results were presented in both cases.

Chen & Ho [23] considered the multiobjective production planning problem within the context of a flexible manufacturing system. They provided a mathematical formulation of the problem that aimed to simultaneously minimize the total flow time, balance machine workload, minimize machine workload and minimize total equipment cost. A suitably encoded EMO algorithm was proposed for the solution of the problem. The algorithm was based on the GMOEA algorithm introduced by Ho and Chang [24]. The algorithm was tested on a number of benchmark problems taken from the literature and performed favorably in comparison with the SPEA multiobjective optimization algorithm [8].

Finally Cochran and Chen [25] addressed the multiobjective version of the daily production planning problem. Three objectives were considered: Effective Work-In Progress (WIP), on-time delivery and bottleneck loading. Typical heuristic procedures were initially employed for the generation of daily production plans according to individual criteria. A binary encoded evolutionary computation algorithm was then used to generate a combination of weights that simultaneously optimized all criteria considered.

IV. Cellular Manufacturing

The configuration and operation of cellular manufacturing systems constitutes a major area of production research for a time period spanning almost four decades. The optimization of manufacturing cells involves the solution of difficult grouping and facility layout problems that provide a challenging environment for any optimization algorithm. From its early days of existence, evolutionary computation research has provided a wealth of solution methodologies for cellular manufacturing problems [2]. In a number of these optimization techniques the case of multiple optimization criteria is explicitly considered. These approaches are discussed in more detail in the following paragraphs.

Venugopal and Narendran [26] presented the first attempt to solve a cell-formation problem with the help of an evolutionary computation algorithm. They also proposed the first evolutionary optimization algorithm that explicitly considered the multiobjective version of the problem. The real-valued solution representation that they employed became the standard representation for the majority of subsequent approaches. Multiobjective optimization was handled through the evolution of two different subsets of populations, one for each objective considered (minimization of total intercell moves and minimization of within-cell load variation).

Gupta et al. [27] employed the same genetic representation of solutions as Venugopal and Narendran but followed a different multiobjective optimization approach for the simultaneous minimization of the total number of intercell - intracell moves and within-cell load variation. Strings with the same genetic material, evolved through the evolutionary computation machines for the solution of the independent single-objective problems, were proposed as potential solutions for the multiobjective case. The same approach was proposed by Onwubolu and Matingi [11] in their scheduling optimization algorithm that was reported earlier.

Morad and Zalzala [28] approached the multiobjective version of the cell-formation problem using a typical weighted-sum combination of the optimization criteria. In addition to the minimization of total moves and cell-load variation, the maximization of machine similarity was also considered as an optimization objective.

Gravel et al. [29] discussed in detail the nature of the multiobjective cell-formation problem and presented an EMO algorithm for its solution. The objectives used were the minimization of intercell moves and the minimization of total within-cell load variation. The proposed methodology accommodated the existence of multiple routes for parts to be processed using a double-loop solution encoding scheme. The epsilon constraint approach and the weighted-sum approach were employed for the simultaneous optimization of objectives.

Hsu and Su [30] developed a comprehensive mathematical model of the multiobjective cell-formation problem that explicitly considered the total production cost (intercell - intracell transportation, machine investment cost, intercell machine loading unbalance, and intracell machine loading unbalance). A weighted-sum evolutionary multiobjective optimization approach that utilized the typical real-valued representation was proposed for the solution of the problem.

Dimopoulos and Zalzala [31] presented an EMO that was custom-designed for the solution of a cell configuration problem in a manufacturing facility of a pharmaceutical company. The variable-length solution encoding accommodated machine-cell assignments and custom genetic operators ensured the validity of solutions. Multiobjective optimization was achieved through the Pareto-ranking based approach originally introduced theoretically by Goldberg [32].

Zhao and Wu [33] discussed a version of the cell-formation problem that explicitly considered sequencing of operations and machine workloads. The proposed model attempted the simultaneous optimization of three objectives: minimization of total moves (intercell and intracell), minimization of cell load variation and minimization of exceptional elements (operations that take place outside the designed cells). An EMO algorithm with typical real-valued representation attempted the simultaneous optimization of objectives through the use of a weighted-sum approach. One of the main features of the proposed methodology was the explicit consideration of multiple routes for parts to be processed. The validity of the proposed approach was illustrated on a number of test problems taken from the literature. Asokan et al. [34] approached a similar version of the multiobjective cell-formation problem using a weighted-sum evolutionary multiobjective optimization algorithm.

Finally, Mansouri et al. [35] developed a comprehensive mathematical model for the multiobjective cell-formation problem that explicitly considered the simultaneous minimization of intercellular part movements, total cost of machine duplication and subcontracting, overall machine under-utilization and deviation among cell-utilization. Solutions were generated with the help of a Pareto-ranking EMO technique called XGA. The solution representation encoded the binary variables of the proposed mathematical model. The algorithm combined sharing elements of the NSGA approach with elitism principles for the set of non-dominated solutions. The proposed algorithm performed favorably in comparison with the VEGA, NSGA and NPGA [36] techniques on a number of test problems taken from the literature. The number and diversity of evolved non-dominated solutions as well as CPU time were used as quality measures for comparison purposes.

V. Flexible Manufacturing Systems

Flexible Manufacturing Systems (FMS) constitute an efficient production system for job-shop manufacturing environments. A group of Computer Numerically Controlled (CNCs) machines and robots interconnected via a number of Automated Guided Vehicles (AGVs) provide flexibility in handling a variety of processing tasks. The installation and productive operation of an FMS requires the solution of difficult process planning, scheduling, and tool allocation problems. Some of these problems have been tackled successfully with the help of evolutionary computation methods [2]. The most significant EMO methodologies that have been proposed in this area are described in the following paragraphs:

Rai et al. [37] considered a complex problem in the area of FMS that addresses the selection of machine tools and the allocation of operations to individual machines. A fuzzy goal programming formulation of the problem was proposed in order to deal with the intrinsic uncertainty about the parameters of the problems. The aim was the simultaneous minimization of the total machining cost, the total setup cost and the total material handling cost. A typical EMO that encoded both the operational and tool allocation variables was employed for the solution of the problem. The objective function utilized a weighted-sum aggregating combination of all three objective functions of the fuzzy goal-programming model. A numerical example was provided to illustrate the efficiency of the proposed methodology.

Tiwari and Vidyarthi [38] discussed the machine loading problem in the context of FMS, i.e. the problem of allocating operations to individual machines. They considered both single and multiobjective cases of the problem. In the latter case the objectives were the minimization of system unbalance and the maximization of throughput, a pair of objectives that are conflicting in nature. A sequence-encoded evolutionary algorithm was employed for the solution of the problem. The algorithm was tested against existing solution methodologies on a number of problems taken from the literature and performed favorably.

VI. Assembly Line Optimization

Assembly lines are widespread in modern manufacturing environments. The manufacturing of a large number of products requires some kind of assembly operation at some stage of the production process. Assembly line optimization requires the solution of difficult sequencing and line balancing problems. Evolutionary computation methods have provided useful contributions to the solution of these problems [2]. A number of researchers have recently developed EMO techniques for the solution of problems in the area of assembly line optimization. These techniques are described in the following paragraphs:

Lit et al. [39] addressed the problem of finding an optimal sequence for assembling a product. A sequence-based evolutionary algorithm was employed for the solution of the multiobjective version of the problem which explicitly considered five objectives: number of reorientations, stability of subsets, parallelism between operations, latest and earliest components to be put in the assembly plan. A purpose-based mapping algorithm ensured that any chromosome produced through the evolutionary process resulted in a valid assembly sequence. The simultaneous optimization of objectives was achieved by incorporating the PROMETHEE-II multicriteria decision making technique [40] within the evolutionary process. The proposed approach resulted in the aggregation of objective values for all objectives considered. The efficiency of the algorithm was illustrated with the help of an industrial assembly sequence planning problem.

Ponnambalam et al. [41] considered the multiobjective assembly line balancing problem. They employed the EMO process originally introduced by Murata and Ischibuchi [3] that assigns randomly generated weights to individual objectives during the optimization run. The objectives considered were the number of stations generated, the smoothness index and line efficiency. Their representation scheme encoded heuristic rules in chromosome positions that were responsible for the assignment of tasks to individual workstations. The algorithm performed favorably in comparison with existing heuristic rules on the solution of the problem considered.

Finally, McMullen et al. [42] discussed the multiobjective case of the mixed-model assembly line sequencing problem within the context of a Just-In-Time production system. The objectives to be simultaneously minimized were the total number of set-ups and the usage rate. These objectives were conflicting in nature and a weighted-sum evolutionary technique was employed for their simultaneous optimization. The proposed methodology was tested on a number of benchmark problems against a Tabu search and a Simulated Annealing algorithm. The evolutionary algorithm clearly outperformed Tabu Search; however, its performance difference with Simulated Annealing could not be distinguished statistically. The mixed-model assembly line sequencing problem was also addressed by Hyun et al. [43]. They introduced a novel EMO technique for the solution of the problem, based on the principles introduced by Goldberg and the niching technique of Horn and Nafpliotis [36]. The objectives considered were the minimization of total utility work, the leveling of part usage and the minimization of total setup cost. The proposed algorithm performed favorably in comparison with Shaffer' VEGA and Horn's NPGA on a number of test problems taken from the literature. A simple aggregating weighted-sum evolutionary computation technique was also proposed by Celano et al. [44] for the solution of a similar problem that simultaneously considered the minimization of the flow line fluctuation and the total line stop time.

VII. Conclusions

Recent research findings suggest that evolutionary computation methods constitute a valuable tool for the solution of multiobjective optimization problems. Their inherent ability of searching the solutions' space from a population of points in parallel provides an excellent basis for the quick exploration of the Pareto front. At the same time, significant research efforts have led to the development of efficient EMO algorithms that overcome problems of genetic diversity and premature convergence.

This paper examined the impact of EMO methodologies in the area of manufacturing optimization. The EMO research field has been growing rapidly over the last few years and a considerable number of associated applications have been reported in various production research areas. The review of these approaches has yielded a number of interesting findings:

In the majority of applications considered, multiobjective optimization was achieved either through aggregation of the optimization objectives [3], [21], [30], [37], [41], evolution of objective-targeted subpopulations [9], [15], [26], or case-based algorithms that utilized the principle of Pareto ranking and the concepts of niching and elitism [18], [23], [31], [35], [43]. Only a limited number of researchers utilized the benefits of typical well-tested EMO methodologies such as NSGA or MOGA [12], [16]. Furthermore, research in this area has yet to catch up with the latest EMO developments that had led to the development of techniques such as NSGA-II and SPEA-II [45].

The application of evolutionary computation methods in realistic production environments has never matched the corresponding research efforts. In the case of EMO, a limited number of case-study applications have been reported, mainly in the area of scheduling [16], [18], [19]. One of the reasons that possibly restrain the use of EMO methodologies in production environments might be the lack of a standard off-the-shelf EMO commercial package that can be used by technicians with limited knowledge of evolutionary computation principles. The lack of a major commercial application that will popularize the use of evolutionary computation methods should also be noted. Application frameworks like the generic scheduler introduced by Khoo et al. [19] constitute a promising step towards the commercial exploitation of research findings in the area of evolutionary computation.

Based on the findings of this review, there are a number of areas that provide grounds for future research activities:

While existing EMO applications cover a variety of production research areas, a considerable number of multiobjective manufacturing optimization problems are currently handled inefficiently through traditional optimization methods. The task of implementing and testing novel or existing EMO methodologies on these manufacturing optimization problems constitutes a significant research direction.

State-of-the-art EMO methodologies such as NSGA-II and SPEA-II have been reported to provide excellent performance in comparison with earlier EMO methodologies. There are grounds to believe that their application to manufacturing optimization problems will strengthen the impact of EMO techniques in this area of research.

It has been reported that the hybridization of evolutionary computation methodologies with alternative optimization techniques and the incorporation of problem-specific information on the design of the algorithms enhance their performance on the problem considered [2]. These findings have been confirmed by a number of applications reported in this review [5], [6], [9], [13], [14], [37]. The design of novel EMO methodologies that are complemented by alternative optimization techniques and incorporate knowledge of the problem considered can provide useful contributions in the area of multiobjective production research.

It is the author's aim to contact research based on the findings of this review and publish relevant results in the future.

ACKNOWLEDGMENTS

The author would like to thank the reviewers for their helpful comments.

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