

Evolutionary Algorithms for Multi-Criteria Supply Chain Optimization

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Abstract:

MOEAs are popular in multi-objective optimization of supply chain problems in the presence of conflicting criteria (e.g., cost, service, risk). The present paper is a review of prominent MOEAs such as traditional Genetic Algorithms (GA) and modern methods such as NSGA-II, SPEA2, MOEA/D, IBEA, PAES, and NSGA-III, explains their mechanisms of finding Pareto-optimal solutions. We describe the ranking and selection mechanism of each algorithm (e.g., non-dominated sorting in NSGA-II, indicator-based selection in IBEA, decomposition in MOEA/D, strengths and weaknesses (e.g., diversity maintenance, scalability with objectives, and elitism) are discussed. An example of supply chain network design and inventory planning would be used to demonstrate how various algorithms (NSGA-II, SPEA2, IBEA, PAES) can produce different Pareto-fronts in practice. The comparison of performance shows that the choice of algorithms has a significant impact on the quality of solutions and dispersion. The survey ends with the tendencies in the application of MOEAs to supply chains and recommendations on how to address the correct methods.

Keywords:

Multi-objective optimization, Evolutionary algorithms, Supply chain optimization, Pareto front, Multi-criteria decision making, Inventory planning, Network design, Elitism, Diversity preservation.

1. Introduction

The supply chains have a variety of opposing goals (examples are cost-minimization and service level maximization) therefore require multi-criteria decision making. Evolutionary algorithms (EAs) are inherently designed to deal with these trade-offs since a population of candidate solutions evolves concurrently. Classical single-objective Genetic Algorithms (GAs) represent solutions as chromosomes and mutate them by means of selection, crossover, and mutation. To solve many goals, GAs can apply scalarization (weighted sums) or target-purpose schemes (e.g. vector evaluated GA), however, current methods explicitly produce Pareto fronts within a single run. MOEAs use Pareto dominance to rank and select solutions; one such method is NSGA-II [1] where rank depends on nondomination levels and crowding distance is used to preserve diversity. Many MOEAs have been created in the past twenty years. Initial applications (e.g. MOGA by Fonseca and Fleming) proved that the evolutionary multi-objective search can be viable. Subsequent algorithms such as NSGA-II [1] added elitism and effective sorting, and others (SPEA2 [2], IBEA [4], MOEA/D [5] and so on) added new selection or decomposition schemes. MOEAs have been used in supply chain optimization, to solve problems including the selection of suppliers, inventory planning, network design and in many cases have provided high-quality trade-offs between cost, service level, and risk [6,7,8]. This paper will review the

important MOEAs, their mechanism, and compare the performance and applicability to the supply chain issues.

2. Literature review

The evolutionary multi-objective optimization has a long history (e.g. surveys by Coello and others) of focusing on Pareto-based ranking where diversity mechanisms are in place. MOEAs can be used in supply chains, as a number of studies depict. As an example, Turk et al. used NSGA-II, SPEA2 and IBEA to a supplier selection and inventory planning problem involving tradeoffs between operation cost and supplier risk [6]. They established that parameter tuning played a very vital role and generally NSGA-II generated the widest Pareto set. Brintrup and Puchkova researched the problem of plant-product distribution in the automotive industry, the cost and network reliability are to be optimized [7]. They addressed this using NSGA-II, SPEA2 and PAES in which it was seen that NSGA-II produced the most extensive Pareto distribution and that the choice of algorithm had a substantial influence on outcomes. Amodeo et al. used NSGA-II (evaluated with a simulation model) on just-in-time distribution network and optimized inventory cost and service level and has demonstrated that it performs well in comparison with current policies [8]. These case studies indicate that MOEAs can successfully produce trade-offs when designing a supply chain, but that various algorithms produce various fronts in solutions. We thus analyze the key MOEA techniques in order to learn their nature.

3. Review of Evolutionary Algorithms

3.1 Genetic Algorithm (GA)

The Genetic Algorithm (GA) is a classical population-based evolutionary search that applies selection, crossover, and mutation to evolve candidate solutions. It maintains a pool of encoded solutions (chromosomes) and repeatedly selects fitter individuals to breed offspring with genetic operators. GA's strengths include flexibility and parallel exploration of the search space, making it broadly applicable. However, standard GA is inherently single-objective and relies on scalarization (e.g. weighted sums or VEGA) to handle multiple goals, which may fail to capture the entire Pareto front without careful tuning [1].

3.2 Nondominated Sorting Genetic Algorithm II (NSGA-II)

NSGA-II [1] is an elitist multi-objective extension of GA that uses nondominated sorting and a crowding-distance metric to guide selection. At each generation it ranks combined parent and offspring populations into Pareto fronts and fills the next population by ascending front rank, breaking ties by preferring individuals in less crowded regions of objective space. Its elitist mechanism preserves high-quality solutions, and its crowding-distance ensures diversity without extra parameters. NSGA-II reliably finds a well-spread Pareto front in few-objective problems,

but its $O(MN^2)$ sorting complexity (with population size N and M objectives) limits scalability and performance as problem size or number of objectives grows [1].

3.3 Strength Pareto Evolutionary Algorithm 2 (SPEA2)

SPEA2 [2] maintains an external archive of nondominated solutions and assigns fitness based on a strength (dominance count) and density estimate. Each individual's fitness reflects how many solutions it dominates plus a k -nearest-neighbor density factor, and the archive ensures elitism across generations. These features give SPEA2 fine-grained selection pressure and often lead to good convergence and distribution along the Pareto front. However, managing the archive and computing fitness values adds computational overhead, and truncation of the archive (when it exceeds its fixed size) can bias the search toward central solutions at the expense of extremes [2].

3.4 Multiobjective Evolutionary Algorithm based on Decomposition (MOEA/D)

MOEA/D [5] decomposes a multi-objective problem into many scalar subproblems via a set of weight vectors or reference directions. Each subproblem optimizes an aggregation (e.g. weighted-sum or Tchebycheff) of objectives, and neighboring subproblems cooperate by sharing solutions. This decomposition lets MOEA/D scale effectively to a larger number of objectives and focus search effort in different regions of the Pareto front. Its advantages include parallelism and adaptability to problem structure, but its performance depends heavily on a well-chosen set of weight vectors; poor weight distribution or normalization can lead to gaps or bias in the obtained Pareto front [5].

3.5 Indicator-Based Evolutionary Algorithm (IBEA)

IBEA [4] replaces Pareto dominance ranking with explicit quality indicators (such as hypervolume or epsilon-indicator) to evaluate and compare solutions. Each individual's fitness is computed from pairwise indicator values, effectively optimizing a chosen performance metric directly. This indicator-driven selection provides flexibility and often yields high-quality Pareto approximations in terms of the selected criterion. The drawbacks of IBEA are its high computational cost (especially for expensive indicators like hypervolume) and sensitivity to the chosen indicator; the search may become biased toward regions favored by that indicator and may suffer scaling issues with many objectives [4].

3.6 Pareto Archived Evolution Strategy (PAES)

PAES [3] is a simple (1+1) evolutionary strategy that maintains a fixed archive of nondominated solutions. In each iteration, one offspring is generated by mutating the current solution; the offspring is admitted to the archive if it is nondominated, possibly replacing a similar archived solution based on a grid-niching rule. The grid-based archive promotes diversity by only accepting new solutions that improve coverage of objective space. PAES has a low memory footprint and can be effective on moderate-scale problems, but its reliance on a single solution

for search means exploration is limited; it often converges more slowly and finds fewer Pareto-optimal solutions than population-based MOEAs [3].

3.7 NSGA-III

NSGA-III [9] generalizes NSGA-II to many-objective problems (typically more than three objectives) by introducing a predefined set of reference points (directions). After nondominated sorting, it selects among the last front by projecting solutions onto these reference lines and choosing those that improve representation in sparsely covered directions. This reference-point-driven niching preserves diversity in high-dimensional objective spaces more effectively than crowding distance. NSGA-III can produce well-distributed Pareto fronts in many-objective scenarios, but it requires careful design of the reference point set and adds algorithmic complexity; its performance depends on matching the reference structure to the problem's characteristics [9].

4. Case Study:

Optimization of the Supply Chain Network. An example of the application of a multi-objective supply chain network design issue and its performance under different MOEAs is the Brintrup and Puchkova optimization of a plant-product automotive network with cost versus reliability, where NSGA-II, SPEA2, and PAES are used, and all managed to get valid solutions with Pareto-optimal fronts; however, the spread of the Pareto-front was maximum with NSGA-II, which shows the influence of the choice of the solution algorithm on the performance [7]. Likewise, Turk et al. applied NSGA-II, SPEA2 and IBEA to supplier selection and inventory management, with selecting a supplier, trading off total supply chain cost versus supplier risk, and IBEA as an indicator model gave a similar fitness as the others, though ultimately the highest quality of trade-offs was obtained using NSGA-II [6]. Amodeo et al. in another study used NSGA-II on a just-in-time distribution network and demonstrated that the algorithm can result in an inventory policy that is more cost and service effective than the current strategies used by the company [8]. Throughout these examples, MOEAs are proven to be effective but vary in their trade-offs exploration: NSGA-II is effective at spreading and elitism, SPEA2 is effective at providing fine-grained ranking with its archive, MOEA/D is effective at scaling, IBEA is effective at indicator-based convergence, and NSGA-III is effective in many-objective scenarios with reference points [9]. Practically, supply chain managers can choose algorithms depending on the dimensionality and complexity, i.e., NSGA-II and SPEA2 with 2-3 objective problems, and NSGA-III or MOEA/D with high-dimensional trade-off landscapes, and can run several MOEAs at once to increase robustness and trust in the obtained solutions.

5. Conclusion:

Evolutionary algorithms based on multi-objective optimization provide a versatile platform in the decision-making process of complex supply chains and provide groups of trade-off solutions

at the same time. Some of the key MOEAs such as the entry-level Genetic Algorithm through to advanced ones such as NSGA-II/III, SPEA2, MOEA/D, IBEA, and PAES have been surveyed and their technical methods and selection processes discussed. The strengths of each algorithm are as follows: NSGA-II is characterized by elitist sorting, SPEA2 is characterized by an archive scheme, MOEA/D is characterized by decomposition, IBEA by indicator metrics, PAES by simplicity, and NSGA-III by a large number of objectives. The weaknesses differ between the cost of computation and sensitivity of the parameter. The case studies in supply chain entail empirical comparisons which reveal that there is no single approach that prevails. Supply chain optimization trends are moving towards hybrid (MOEAs with simulation or local search), many-objective, and domain-specific optimizations (e.g., fuzzy criteria). All in all, MOEAs have continued to be an effective instrument in supply chain multi-criteria decision problems. The choice of the right algorithm varies with the number of goals, the desired Pareto dispersion, and the computational capabilities. Future development can focus on automated algorithm configuration and interactive MOEAs that update preferences of the decision-maker in real time.

6. References

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