Metaheuristics for Multiobjective Optimization _{Ch 4.1 - 4.2}

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MULTIOBJECTIVE OPTIMIZATION CONCEPTS

Multiobjective optimization problems (MOP)

- There are many conflicting objectives to handle
- Pareto optimal solution
 - It is not possible to improve a given objective without deteriorating at least another objective
- Mostly focused on P-metaheuristics

MOP

$$MOP = \begin{cases} \min F(x) = (f_1(x), f_2(x), \dots, f_n(x)) \\ s.c. \ x \in S \end{cases}$$

- x = (x₁, ..., x_k): vector representing the decision variables
- S: the set of feasible solutions
- F(x): the vector of objectives to be optimized

Decision space and objective space



FIGURE 4.1 Decision space and objective space in a MOP.

Definition 4.2 Pareto dominance. An objective vector $u = (u_1, ..., u_n)$ is said to dominate $v = (v_1, ..., v_n)$ (denoted by $u \prec v$) if and only if no component of v is smaller than the corresponding component of u and at least one component of u is strictly smaller, that is,

 $\forall i \in \{1, ..., n\}$: $u_i \leq v_i \land \exists i \in \{1, ..., n\}$: $u_i < v_i$



Definition 4.3 Pareto optimality. A solution $x^* \in S$ is Pareto optimal⁴ if for every $x \in S$, F(x) does not dominate $F(x^*)$, that is, $F(x) \not\prec F(x^*)$.

Definition 4.4 Pareto optimal set. For a given MOP (F, S), the Pareto optimal set is defined as $\mathcal{P}^* = \{x \in S / \nexists x' \in S, F(x') \prec F(x)\}.$

Pareto front

Definition 4.5 Pareto front. For a given MOP (F, S) and its Pareto optimal set \mathcal{P}^* , the Pareto front is defined as $\mathcal{PF}^* = \{F(x), x \in \mathcal{P}^*\}$.

- The image of the Pareto optimal set in the objective space
- The main goal of MOP

Desired Pareto front



FIGURE 4.3 Examples of Pareto fronts: bad convergence and good diversity (left), good convergence and bad diversity (center), good convergence and diversity (right).

Definition 4.6 Ideal vector. A point $y^* = (y_1^*, y_2^*, \dots, y_n^*)$ is an ideal vector if it minimizes each objective function f_i in F(x), that is, $y_i^* = \min(f_i(x)), x \in S, i \in [1, n]$.

Definition 4.7 Reference point. A reference point $z^* = [\overline{z}_1, \overline{z}_2, ..., \overline{z}_n]$ is a vector that defines the aspiration level (or goal) \overline{z}_i to reach for each objective f_i .

Definition 4.8 Nadir point. A point $y^* = (y_1^*, y_2^*, \dots, y_n^*)$ is the nadir point if it maximizes each objective function f_i of F over the Pareto set, that is, $y_i^* = \max(f_i(x)), \quad x \in \mathcal{P}^*, i \in [1, n].$

The ideal and nadir points give some information on the ranges of the Pareto optimal front

Definition 4.9 Utility function. A utility (or value) function v, which represents the preferences of the decision maker, maps the objective vector to a scalar-valued function: $v : \mathbb{R}^n \longrightarrow \mathbb{R}$.

Definition 4.10 Locally Pareto optimal solution. A solution x is locally Pareto optimal if and only if $\forall w \in N(x)$, F(w) does not dominate F(x), and N(x) represents the neighborhood of the solution x.

$$(\text{MOP}_{\lambda}) \begin{cases} \min F(x) = \sum_{i=1}^{n} \lambda_i f_i(x) \\ \text{s.c. } x \in S \end{cases}$$

Definition 4.11 Weak dominance. An objective vector $u = (u_1, \ldots, u_n)$ is said to weakly dominate $v = (v_1, \ldots, v_n)$ (denoted by $u \leq v$) if all components of u are smaller than or equal to the corresponding components of v, that is, $\forall i \in \{1, \ldots, n\}$, $u_i \leq v_i$ (Fig. 4.5).

Definition 4.12 Strict dominance. An objective vector $u = (u_1, ..., u_n)$ is said to strictly dominate $v = (v_1, ..., v_n)$ (denoted by $u \prec \prec v$) if all components of u are smaller than the corresponding components of v, that is, $\forall i \in \{1, ..., n\}$, $u_i < v_i$

Definition 4.13 ϵ -Dominance. An objective vector $u = (u_1, \ldots, u_n)$ is said to ϵ -dominate $v = (v_1, \ldots, v_n)$ (denoted by $u \prec_{\epsilon} v$) if and only if no component of v is smaller than the corresponding component of $u - \epsilon$ and at least one component of $u - \epsilon$ is strictly better, that is, $\forall i \in \{1, \ldots, n\} : u_i - \epsilon_i \le v_i \land \exists i \in \{1, \ldots, n\} : u_i - \epsilon_i \le v_i \land \exists i \in \{1, \ldots, n\} : u_i - \epsilon_i < v_i$ (Fig. 4.6).



Weak dominance and strict dominance concepts. Solution u weakly dominate solution v; solution u' weakly dominates solution v'; solution u strictly dominates solutions v' and v''.



Categories and applications

- Two categories:
 - continuous
 - discrete
- Academic applications
 Real-Life applications

Academic applications [¬] Multiobjective Continuous Problems

min $F(x) = (f_1(x), f_2(x), \dots, f_n(x))$

subject to

 $g_i(x) \le 0, \quad i = 1, ..., m$ $h_i(x) = 0, \ i = 1, ..., p$

Well-known test problems (standard benchmarks):

ZDTDTLZ

Academic applications

- Multiobjective Combinatorial Problems
 - Iack of "standard" benchmarks
 - Two complexity categories:
 - Polynomial problems: shortest path, spanning tree problems, assignment problems
 - NP-hard problems: scheduling problems, routing problems

Multiobjective scheduling problems

<i>M</i> ₁	J ₂	J ₄	J ₅		<i>J</i> ₁	J ₆		<i>J</i> ₃					
<i>M</i> ₂		<i>J</i> ₂	<i>J</i> ₄		J ₅		<i>J</i> ₁		J	6	J ₃		
<i>M</i> ₃				1 ₂		J	J ₅		<i>J</i> ₁		J ₆	<i>J</i> ₃	

- C_{\max} Makespan (total completion time): $\max\{C_i | i \in [1 \dots n]\}$
- C: Mean value of jobs completion time
- T_{\max} : Maximum tardiness: max{ $[\max(0, C_i d_i)] | i \in [1...n]$ }
- T: Total tardiness: $\sum_{i=1}^{n} [\max(0, C_i d_i)]$
- U: Number of jobs delayed with regard to their due date d_i
- F_{max} : Maximum job flow-time: max $\{C_i r_i | i \in [1 \dots n]\}$
- F: Mean job flow-time

Real-life applications

- Engineering design
- Environment and energetics
- Telecommunications
- Control
- Computational biology and bioinformatics
- Transportation and logistics

Multicriteria decision making

- There is a need for interaction between the decision maker and the problem solver:
 - A priori
 - A posteriori
 - Intercative

