Multi-Stakeholder Non-Dominated Sorting Genetic Algorithm-II: Beyond Single Decision Maker Optimization

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Abstract

Evolutionary multi-objective optimization (EMO) is widely used to solve problems with competing objectives, yet most existing approaches assume a single decision maker and offer limited support for the diverse and often incomplete preferences found in multi-stakeholder settings. We introduce MS-NSGA-II, an extension of NSGA-II that incorporates heterogeneous stakeholder aspirations without requiring negotiation or repeated interaction. Stakeholders specify only the objectives and aspiration levels relevant to them, and a normalized dissatisfaction measure guides selection while preserving the underlying multi-objective formulation and maintaining diversity in the objective space. Experiments on benchmark problems with up to ten objectives and a real-world area design case study show that MS-NSGA-II significantly reduces stakeholder dissatisfaction and uncovers Pareto-superior regions, particularly in higher-dimensional settings.

CCS Concepts

• **Applied computing → Multi-criterion optimization and decision-making**; • **Theory of computation → Evolutionary algorithms**.

Keywords

Multi-objective optimization, Preference-based optimization, Group decision making, NSGA-II

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1 Introduction

Evolutionary multi-objective optimization (EMO) methods have been extensively studied to solve real-world optimization problems with conflicting objectives. Formally, a multi-objective optimization problem can be written as

$$\min \; f(x) = \big(f_1(x), \ldots, f_m(x)\big) \qquad x \in X, \tag{1}$$

where $X \subseteq \mathbb{R}^n$ denotes the feasible decision space and f_i are m potentially conflicting objective functions to be minimized. Among EMO algorithms, the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) [7] is widely used due to its ability to produce converged and diverse approximations of the entire Pareto front.

In many practical applications, a decision maker (DM) is interested only in specific regions of the Pareto front, motivating preference-based EMO methods. A priori approaches, in which preferences are specified once before the search starts, are particularly attractive in practice, as they avoid repeated interaction during optimization. A prominent class of such methods is reference point-based EMO, including R-NSGA-II [8], where aspiration points guide the search toward preferred trade-offs. Related approaches bias the search using reference directions [5, 6] or region-of-interest formulations [12], while interactive methods infer preferences from comparisons or classifications [2, 3, 15]. These methods, however, are typically formulated for settings with a single decision maker who evaluates all objectives.

In contrast, many real-world optimization problems involve multiple stakeholders with heterogeneous and possibly conflicting preferences [4], yet only a few EMO approaches explicitly address such

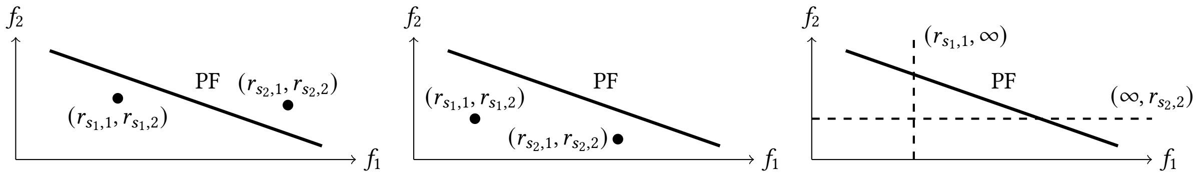

Figure 1: 2D examples with two stakeholders (s_1, s_2): (a) one aspiration lies below the Pareto front and one above; (b) both aspirations lie below the Pareto front; (c) each stakeholder specifies a single aspiration value, producing simple reference lines.

settings [14]. Existing methods aggregate preferences into a single objective [11], rely on negotiation or consensus mechanisms [1, 13], or adopt interactive preference-learning frameworks that require repeated elicitation, assume joint relevance of all objectives, and depend on theoretical normalization bounds [10, 16]. These assumptions limit scalability and hinder reliable preference modeling when preferences are incomplete or objective ranges are unknown.

To address these limitations, we propose the Multi-Stakeholder Non-Dominated Sorting Genetic Algorithm-II (MS-NSGA-II). The method allows each stakeholder to specify only objectives they consider relevant, together with corresponding aspiration levels, enabling heterogeneous and incomplete preference information. Stakeholder dissatisfaction is quantified using a normalized measure and aggregated via a tunable ℓ_p formulation, providing explicit control over the trade-off between efficiency and fairness. An ϵ-based grouping strategy preserves diversity. Benchmark experiments and a real-world area design case study demonstrate that MS-NSGA-II substantially reduces stakeholder dissatisfaction and scales effectively to many-objective settings.

2 Methodology

2.1 MS-NSGA-II

The MS-NSGA-II extends the NSGA-II framework by integrating stakeholder preferences through a dissatisfaction-guided-survival mechanism. The other components of NSGA-II, including crossover, mutation, and non-dominated sorting, are kept. Each stakeholder $s \in \mathcal{S} := \{1, \ldots, S\}$ specifies non-negative objective weights $w_s = (w_{s,1}, \ldots, w_{s,m})$ and aspiration levels $r_s = (r_{s,1}, \ldots, r_{s,m})$, following the preference model of Hu and Mehrotra [9]. Objectives deemed irrelevant are encoded by setting $w_{s,i} = 0$ and $r_{s,i} = \infty$.

The dissatisfaction of stakeholder s with solution x is defined as

$$d_s(x) = \sum_{i=1}^{m} w_{s,i} \max\{f_i(x) - r_{s,i},\ 0\}, \tag{2}$$

which penalizes only violations of stakeholder-specific aspiration levels, weighted by objective relevance. To ensure comparability across objectives, dissatisfaction is evaluated using population-based normalization of objective values and aspirations:

$$\tilde{f}_i(x) = \frac{f_i(x) - f_i^{\min}}{f_i^{\max} - f_i^{\min}}, \quad \tilde{r}_{s,i} = \frac{r_{s,i} - f_i^{\min}}{f_i^{\max} - f_i^{\min}}. \tag{3}$$

As in NSGA-II, complete non-dominated fronts are added to the population until the final front F exceeds the population budget. Selection from F is guided by the aggregated dissatisfaction measure

$$\Phi_p(x) = \left(\sum_{s=1}^{S} \lambda_s \tilde{d}_s(x)^p \right)^{1/p}, \tag{4}$$

where $p \in [1, \infty]$ interpolates between average ($p = 1$) and worst-case ($p \to \infty$) dissatisfaction, and $\lambda_s > 0$ reflects the importance of stakeholder s in the decision process.

To maintain diversity, we apply an ϵ-based grouping similar to R-NSGA-II [8]. Selection from the final front F proceeds as follows: (1) all solutions $x \in F$ are sorted in ascending order of Φ_p; (2) solutions are grouped if their normalized L_1-distance satisfies $\sum_{i=1}^{m} |\tilde{f}_i(x) - \tilde{f}_i(y)| \leq \epsilon$; (3) from each group, the solution with the smallest Φ_p is selected; and (4) if slots remain, they are filled with the remaining solutions in order of increasing Φ_p.

Figure 1 exemplifies three situations addressed by MS-NSGA-II. In the first, an aspiration above the Pareto front is automatically satisfied, and the search focuses on reducing dissatisfaction for the other stakeholder. In the second, two aspirations lie below the front, requiring a balanced compromise. In the third, stakeholders specify aspirations only for objectives they consider relevant, yielding reference lines in two dimensions that generalize to complex manifolds in higher dimensions, a setting that is difficult for existing methods to represent but is naturally accommodated by MS-NSGA-II.

2.2 R-NSGA-II Baselines

To assess the effect of dissatisfaction-guided survival selection, we benchmark MS-NSGA-II against R-NSGA-II. As a reference point-based algorithm that integrates aspirations directly into survival selection, R-NSGA-II provides a natural baseline.

To enable a fair comparison with MS-NSGA-II, we consider two adaptations of R-NSGA-II. The first aggregates stakeholder aspirations into a single proxy reference point:

$$\tilde{r}_i^{\text{proxy}} = \frac{\sum_s \lambda_s w_{s,i} \tilde{r}_{s,i}}{\sum_s \lambda_s w_{s,i}}. \tag{5}$$

The second assigns each stakeholder a reference point, using a neutral value (1/2) for objectives they do not consider relevant:

$$\tilde{r}_{s,i}^{\text{multi}} = \begin{cases} \tilde{r}_{s,i} & \text{if } w_{s,i} \neq 0, \\ \frac{1}{2} & \text{otherwise.} \end{cases} \tag{6}$$

Although these procedures extend R-NSGA-II to multi-stakeholder settings, they still compress heterogeneous preferences into one or more reference points, whose relevance is ambiguous when the Pareto front is unknown.

Table 1: Stakeholder weight and aspiration configurations.

Problem	s	Configuration (w_s, r_s)
ZDT1	$\{1, 2\}$	$((1, 1), (0.2, 0.4));\ ((1, 1), (0.8, 0.4))$
ZDT2	$\{1, 2\}$	$((1, 1), (0.1, 0.8));\ ((1, 1), (0.8, 0.2))$
ZDT3	$\{1, 2\}$	$((1, 1), (0.1, 0));\ ((1, 1), (0.5, -0.75))$
DTLZ2-3	1	$((1, 1, 1), (0.75, 0.75, 0.25))$
	2	$((0, 1, 1), (\infty, 0.2, 0.2))$
	3	$((1, 1, 0), (0.2, 0.2, \infty))$
DTLZ2-5	1	$((1, 1, 1, 0, 0), (0.2, 0.2, 0.2, \infty, \infty))$
	2	$((0, 1, 1, 1, 1), (\infty, 0.2, 0.2, 0.2, 0.8))$
	3	$((0, 0, 0, 1, 1), (\infty, \infty, \infty, 0.1, 0.1))$
DTLZ2-10	1	$((1, 1, 1, 1, 1, 1, 0, 0, 0, 0)$ $(0.2, 0.2, 0.2, 0.2, 0.2, 0.2, \infty, \infty, \infty, \infty))$
	2	$((0, 0, 0, 1, 1, 1, 0, 0, 0, 0)$ $(\infty, \infty, \infty, 0.1, 0.1, 0.1, \infty, \infty, \infty, \infty))$
	3	$((0, 1, 1, 1, 1, 1, 1, 1, 1, 1)$ $(\infty, 0.2, 0.2, 0.2, 0.2, 0.2, 0.2, 0.2, 0.2, 0.2))$

Table 2: Average GD and Φ_p (min/mean/max) for all ZDT and DTLZ2 problems over 20 runs.

	Method	GD	$\Phi_p^{\min}$	Φ_p^{mean}	$\Phi_p^{\max}$
ZDT1	NSGA-II	5.17E−4	1.63E−1	5.33E−1	1.20E0
	R-NSGA-II (S)	1.96E−4	1.78E−1	2.47E−1	4.06E−1
	R-NSGA-II (M)	1.38E−4	1.80E−1	3.15E−1	4.99E−1
	MS-NSGA-II	1.16E−4	1.60E−1	1.84E−1	3.20E−1
ZDT2	NSGA-II	3.74E−4	8.61E−1	9.55E−1	1.10E0
	R-NSGA-II (S)	1.19E−4	9.21E−1	9.45E−1	9.64E−1
	R-NSGA-II (M)	1.10E−4	8.65E−1	9.46E−1	1.03E0
	MS-NSGA-II	5.00E−5	8.60E−1	9.27E−1	9.87E−1
ZDT3	NSGA-II	2.26E−4	7.06E−1	1.10E0	1.61E0
	R-NSGA-II (S)	3.90E−3	7.11E−1	8.78E−1	1.22E0
	R-NSGA-II (M)	1.53E−3	8.48E−1	9.58E−1	1.24E0
	MS-NSGA-II	1.31E−4	7.05E−1	8.46E−1	1.09E0
DTLZ2-3	NSGA-II	9.26E−3	1.02E0	1.64E0	2.06E0
	R-NSGA-II (S)	2.40E−3	1.57E0	1.72E0	1.85E0
	R-NSGA-II (M)	3.15E−3	1.08E0	1.46E0	1.74E0
	MS-NSGA-II	1.33E−3	9.69E−1	1.20E0	1.49E0
DTLZ2-5	NSGA-II	4.40E−1	1.08E0	2.60E0	4.60E0
	R-NSGA-II (S)	2.27E−2	1.75E0	1.91E0	2.03E0
	R-NSGA-II (M)	2.55E−2	1.28E0	1.54E0	1.83E0
	MS-NSGA-II	2.72E−2	7.62E−1	7.68E−1	8.27E−1
DTLZ2-10	NSGA-II	2.22E0	1.94E0	9.00E0	1.58E1
	R-NSGA-II (S)	1.39E−1	1.14E0	1.26E0	1.40E0
	R-NSGA-II (M)	1.39E−1	1.22E0	1.40E0	1.65E0
	MS-NSGA-II	1.42E−1	7.00E−1	7.01E−1	7.09E−1

3 Simulation Results

We evaluate MS-NSGA-II on standard benchmark problems and a real-world-inspired area design case study. All algorithms use SBX crossover (index 10), polynomial mutation (index 20), a population size of 100, and run for 500 iterations, yielding 50100 function evaluations per run (including the initial population); results are averaged over 20 runs. Performance is assessed using aggregated stakeholder dissatisfaction Φ_p and Generational Distance (GD) [17], where lower GD indicates better convergence to the Pareto front.

Benchmark results are reported for $p = 1$ with equal λ_s, corresponding to average dissatisfaction. For the area design case study, where the true Pareto front is unknown, we additionally report hypervolume (HV) [18] (higher indicates better coverage) and consider both $p = 1$ and $p = \infty$ to analyze efficiency-fairness trade-offs.

3.1 Benchmark Problems

We consider six benchmark problems: two-objective ZDT problems and three DTLZ2 problems with increasing dimensionality (3, 5, and 10). Stakeholder configurations are summarized in Table 1, and GD and Φ_p results are reported in Table 2. We use $\epsilon = 0.003$ for the ZDT problems and $\epsilon = 0.03$ for the DTLZ2 problems.

The results show that across all benchmarks, MS-NSGA-II focuses the search on relevant regions of the Pareto front, achieving GD values comparable to R-NSGA-II while consistently attaining lower minimal and mean stakeholder dissatisfaction. This becomes more pronounced for the higher-dimensional DTLZ2 problems.

3.2 Area Design Use Case

We further evaluate MS-NSGA-II on an area design problem inspired by the redevelopment of the Hamerkwartier neighborhood in Amsterdam (Figure 2), involving multiple stakeholders with conflicting sustainability, economic, land-use, housing, and accessibility objectives. The objective vector is defined as

$$f = (CO_2,\ -\mathrm{NCA},\ -\mathrm{BAR},\ -\mathrm{DWL},\ -\mathrm{ACC}), \tag{7}$$

where NCA denotes non-constructed area, BAR building area return, DWL the number of dwellings, and ACC accessibility measured as reachable public transport stops per household; maximization objectives are negated. We consider two diversity settings, $\epsilon = 0.03$ and $\epsilon = 0.3$, to contrast preference focus and exploration.

Figure 2: Hamerkwartier neighborhood and building areas.

We consider three synthetic stakeholders: the municipality (s_1), the developer (s_2), and residents (s_3), with preferences

- s_1: $w_1 = (0.5, 0, 0, 0.3, 0.2),\ r_1 = (300, \infty, \infty, -6.5, -2.5)$,
- s_2: $w_2 = (0, 0, 0.7, 0.2, 0.1),\ r_2 = (\infty, \infty, -8, -11, -1.5)$,
- s_3: $w_3 = (0, 0.4, 0, 0, 0.6),\ r_3 = (\infty, -50, \infty, \infty, -3)$.

Table 3: Average GD, HV, and Φ_p (min/mean/max) for the area design problem over 20 runs.

ϵ	Method	GD	HV	Φ_1^{min}	Φ_1^{mean}	Φ_1^{max}	Φ_∞^{min}	Φ_∞^{mean}	Φ_∞^{max}
0.03	NSGA-II	1.10E0	2.89E5	2.96E−1	7.86E−1	1.49E0	1.26E−1	3.72E−1	6.50E−1
	R-NSGA-II [Single]	0.00E0	1.04E5	2.24E−1	2.42E−1	2.68E−1	1.07E−1	1.21E−1	1.38E−1
	R-NSGA-II [Multi]	6.86E−1	1.68E5	1.87E−1	3.52E−1	6.24E−1	7.21E−2	1.76E−1	3.48E−1
	MS-NSGA-II [p=1]	0.00E0	2.77E5	9.65E−2	1.04E−1	1.15E−1	7.85E−2	8.45E−2	9.02E−2
	MS-NSGA-II [p=∞]	7.11E−4	2.21E5	1.39E−1	1.66E−1	2.01E−1	6.30E−2	6.84E−2	8.47E−2
0.3	NSGA-II	1.10E0	2.89E5	2.96E−1	7.86E−1	1.49E0	1.26E−1	3.72E−1	6.50E−1
	R-NSGA-II [Single]	1.46E0	2.69E5	2.34E−1	4.80E−1	1.14E0	9.73E−2	2.16E−1	5.20E−1
	R-NSGA-II [Multi]	1.23E0	2.95E5	2.67E−1	5.70E−1	1.13E0	1.04E−1	2.62E−1	5.09E−1
	MS-NSGA-II [p=1]	2.30E−1	3.62E5	1.16E−1	3.70E−1	1.04E0	8.06E−2	1.91E−1	4.99E−1
	MS-NSGA-II [p=∞]	5.43E−1	3.40E5	1.63E−1	4.17E−1	9.89E−1	6.92E−2	1.84E−1	4.72E−1

Table 3 shows that MS-NSGA-II achieves lower stakeholder dissatisfaction than NSGA-II and both R-NSGA-II variants across both diversity settings, while maintaining competitive GD and HV. The setting $\epsilon = 0.03$ yields lower Φ_p values, whereas $\epsilon = 0.3$ provides a wider solution range, but still outperforms NSGA-II and R-NSGA-II in terms of dissatisfaction. Varying p reveals the efficiency-fairness trade-off, with $p = 1$ minimizing average and $p = \infty$ minimizing maximum dissatisfaction.

4 Conclusion

We presented the MS-NSGA-II, a preference-based EMO algorithm for multi-stakeholder optimization that supports heterogeneous and incomplete preferences by integrating aspiration-based dissatisfaction into survival selection. Benchmark and area design results show lower stakeholder dissatisfaction than NSGA-II and R-NSGA-II while maintaining Pareto convergence and allowing efficiency-fairness trade-offs by tuning p. Future work will expand the experiments, including many-objective baselines, preference-aware indicators, and experiments with more values of p.

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