Research review: a modified micro genetic algorithm for undertaking multi-objective optimization problems

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Research Review
A Modified micro Genetic Algorithm for undertaking Multi-Objective Optimization Problems

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Real-world problems often entail multiple and yet conflicting objectives, known as **Multi-objective Optimization Problems (MOPs)**

Pareto non-dominated solutions:
An optimization phenomenon whereby it is impossible to make any one solution better off without causing at least one solution worse off
Preliminaries

Motivation

Why using **Evolutionary Algorithm** (EA)?

- EAs are useful for tackling optimization problems by exploiting natural selection phenomena and the learning capability of problem solving.

Pareto optimality principle is used to measure the effectiveness of **Multi-Objective Evolutionary Algorithms** (MOEAs) using MOP indicators as follows:

A classification of MOP indicators
This research focuses on tackling MOPs using MOEA-based model.

Specifically, the **micro Genetic Algorithm** (mGA) is used as the base MOEA model, which has salient properties as follows.

- a Genetic Algorithm (GA) evolves with a small population size, i.e. three to six chromosomes
- able to solve non-linear optimization problems
- uses a restart strategy to achieve convergence and to maintain diversity as compared with GA
mGA is used as the building block to design and develop an enhanced model to tackle MOPs, i.e. Modified mGA (MmGA)

The MmGA is evaluated comprehensively using benchmark MOPs
The key research questions is:

- how to improve the convergence properties of the MmGA solutions towards the Pareto front while preserving the salient properties of the original mGA model?

The research objectives is:

- to improve the original mGA model in tackling MOPs with good convergence properties towards the Pareto front
### Literature Review

#### Categories of MOEAs

<table>
<thead>
<tr>
<th>MOEA Category</th>
<th>Usage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decomposition-based</td>
<td>Novel MOEA design and formation (Li and Zhang, 2009; Ke et al., 2013), and arc routing problem (Mei et al., 2011a).</td>
</tr>
<tr>
<td>Indicator-based</td>
<td>Novel MOEA design and formation (Wagner and Trautmann, 2010; Bader and Zitzler, 2011), and nurse scheduling (Basseur et al., 2012).</td>
</tr>
<tr>
<td>Hybrid-based</td>
<td>Novel MOEA design and formation (Elhossini et al., 2010; Yang et al., 2009), vehicle routing problem (Cattaruzza et al., 2013), arc routing problem (Liu, Jiang and Geng, 2013), and traveling salesman problem (Castro et al., 2013).</td>
</tr>
<tr>
<td>Memetic-based</td>
<td>Novel MOEA design and formation (Soliman et al., 2009; Fernandez Caballero et al., 2010), arc routing problem (Mei et al., 2011b), environmental power unit commitment design (Li, Pedroni and Zio, 2013), permutation flow shop scheduling (Chiang et al., 2011), job shop scheduling (Fruutos and Tohmé, 2013).</td>
</tr>
<tr>
<td>Co-evolution-based</td>
<td>Novel MOEA design and formation (Soliman et al., 2009; Wang et al., 2013), ship design (Cui and Turan, 2010), knapsack problem (Jiao et al., 2013).</td>
</tr>
</tbody>
</table>
### Literature Review

**mGA-based models**

<table>
<thead>
<tr>
<th>Year</th>
<th>Model</th>
<th>Characteristics and Usage</th>
</tr>
</thead>
<tbody>
<tr>
<td>2003</td>
<td>mGA2 with an adaptive parameter tuning mechanism (Toscano Pulido and Coello, 2003)</td>
<td>An extended mGA (Coello and Pulido, 2001) for undertaking benchmark MOPs.</td>
</tr>
<tr>
<td>2007</td>
<td>mGA with Newton-Raphson load flow algorithm (Mendoza et al., 2007)</td>
<td>A model used to optimize localization of AVRs.</td>
</tr>
<tr>
<td>2009</td>
<td>mGA with novel encoding and genetic operators (Mendoza et al., 2009)</td>
<td>A model used to optimize power losses and reliability indices in a power distribution system.</td>
</tr>
<tr>
<td>2011</td>
<td>mGA with a fuzzy controller (Chen, 2011)</td>
<td>A model used to optimize parameters of a fuzzy controller for vehicle suspension control design.</td>
</tr>
</tbody>
</table>

### The population sizes in mGA-based models

<table>
<thead>
<tr>
<th>SOP</th>
<th>Size 5: Krishnakumar (1990), Johnson and Abushagur (1995), Smajic et al. (2009), Watanabe et al. (2010), Itoh et al. (2012)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Size 6: Chu et al. (2013)</td>
</tr>
<tr>
<td></td>
<td>Size 7: Ali and Ramaswamy (2009)</td>
</tr>
<tr>
<td></td>
<td>Size 3, 5: Mendoza et al. (2007)</td>
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<tr>
<td></td>
<td>Size 5: Mendoza et al. (2009)</td>
</tr>
<tr>
<td></td>
<td>Size 6: Chen (2011)</td>
</tr>
</tbody>
</table>
The MmGA Model

A flowchart of the proposed MmGA model.
The MmGA Model

- Improving the convergence properties towards to the true Pareto front as compared with mGA using
  - An NSGAII inspired elitism method
  - An extended population formation method

```
Require: Select \( c_0 \) non-dominated fronts based on given inbound individuals \( x' \) where maximum \( |x'| = 2N, |y| \rightarrow \) constant \( c_1 \)

1: Procedure MmGAElitism \((x', y, c_0)\)
2: \( z = \{ \nabla(x' \cap y) \mid z \in x' \} \)
3: \( w = \text{FNDS}(z) \quad /**\text{adopted from (Deb et al., 2002)}/**/ \)
4: \( i = 1 \)
5: while \( i \leq (2N + c_1) \) do
6: \( \text{CDAssignment}(w_i) \quad /**\text{adopted from (Deb et al., 2002)}/**/ \)
7: \( i = i + 1 \)
8: end while
9: \( e = \text{Sort}(w, \preceq_{CD}) \quad /**\text{adopted from (Deb et al., 2002)}/**/ \)
10: return \( \{ e \mid \forall e \in \nabla(x' \cap y) \cup y, |e| = c_0 + c_1 \} \)
```

An NSGA-II inspired elitism strategy.
The MmGA Model

An extended population formation procedure, adapted from Coello and Toscano Pulido (2001); Coello and Pulido (2005).

Require: Generate constant $n$ number of populations based on given inbound and constant $c_0$ members’ adoption rate

1: Procedure InitializePopulation ($n$, $c_0$, irm, rm, m)
2: $\mathbf{p}_{\text{init}} = \text{irm}$
3: $r = \{ [r_1, \ldots, r_n] | \forall r \in \text{random}(N), N = [1, 2, \ldots, n] \}$
4: $d = \{ \text{rm, m} \}$
5: $i = 1$
6: while $i \leq d$ do
7: $z_{\text{unique}} = \{ -\langle d_i \cap \mathbf{p}_{\text{init}} \rangle, \mathbf{p}_{\text{init}} | \leq n, \forall z_{\text{unique}} \in d_i, | z_{\text{unique}} | \leq d_i \}$
8: $z_{\text{sorted}} = \{ \text{Sort}(z_{\text{unique}}, \leq) \}$
9: if $i = 1$ then /* for rm component**/
10: $c_1 = c_0 \times (n - | \text{irm} |)$
11: *Add $c_1$ members from $z_{\text{sorted}}$ to $\mathbf{p}_{\text{init}}$
12: end if
13: if $i = 2$ then /* for m component**/
14: $c_1 = \{ c_0 \times (n - | \mathbf{p}_{\text{init}} |), | \mathbf{p}_{\text{init}} | \neq 0, c_0 > 0 \}$
15: for $j = 1 \rightarrow c_1$ do
16: *Add $(r_j)$th of $z_{\text{sorted}}$ to $\mathbf{p}_{\text{init}}$
17: end for
18: end if
19: $i = i + 1$
20: end while
21: if $| \mathbf{p}_{\text{init}} | \leq n$ then /* for new random elements**/
22: $c_1 = \{ n - | \mathbf{p}_{\text{init}} |, | \mathbf{p}_{\text{init}} | \neq 0, c_0 > 0 \}$
23: for $j = 1 \rightarrow c_1$ do
24: *Add random solution to $\mathbf{p}_{\text{init}}$
25: end for
26: end if
27: return $\mathbf{p}_{\text{init}}$
The MmGA Model

The pseudo-code of the overall MmGA model.

```
Require: Generate non-dominated solutions for MOP
1: Procedure MmGA
2: \( i = 0 \), \( p_{MmGA} = \phi \n\)
3: \( em = f(archiveSize,BiSection,n) = \phi \)
4: Initialize \( m_{init} \)
5: \( +m = Sort(m_{init}, \leq) \)
6: \( \textbf{while} i < \text{evaluation}_{Max} \textbf{do} \)
7: \( +p_{init} = InitializePopulation(n, ratio, irm, rm, m) \)
8: \( +p = Sort(p_{init}, \leq) \)
9: \( \textbf{repeat} \)
10: \( u = \text{Apply binary tournament selection on } p \)
11: \( v = \text{Apply two-Point crossover on } u \)
12: \( w = \text{Apply uniform mutation on } v \)
13: \( p_{i}^{MmGA} = +MmGAElitism(w, p, 1) \)
14: \( \text{until } \text{nominalConvergence}_{Max} \text{ is reached} \)
15: \( em_{MmGA} = +1MmGAElitism(p_{i}^{MmGA}, em, eliteSize) \)
16: \( \text{if } em \text{ is full when trying to insert } em_{elite} \text{ then} \)
17: \( em = adaptiveGrid(em_{elite}) \) /* adopted from (Knowles and Corne, 2000) */
18: \( \text{end if} \)
19: \( m = +2MmGAElitism(p_{i}^{MmGA}, m, eliteSize) \)
20: \( \text{if } i \text{ modulus replacementCycle then} \)
21: \( rm = +3MmGAElitism(em, rm, eliteSize) \)
22: \( \text{end if} \)
23: \( i = i + 1 \)
24: \( \textbf{end while} \)
25: \( \textbf{return } p_{MmGA}^{i} \)
26: /* +1, +2, +3 are the first, second and third forms of elitism mGA, respectively. */
```
**Key result:** It achieved fast convergence in $l_{gd}$ with statistical significance results.

A comparison between $l_{gd}$ of mGA (i.e. dotted lines) and bootstrapped $l_{gd}$ of MmGA. The error bars indicate the 95% confidence intervals of the mean $l_{gd}$ results of MmGA.
The key contributions of this research are as follows:

- Created an enhanced mGA-based models to provide near optimal solutions with reference to the true Pareto front for undertaking MOPs
- Assessed the proposed models with benchmark MOPs and conducted a comprehensive performance comparison with other similar models
Conclusions and Contributions

- Quantified all results with the bootstrap statistical method to confirm the stability of performance (see paper)
- Derived the time complexity analysis using the big-O notation (see paper)
The further works of this research are as follows:

- to attempt to measure the performance of the MmGA using other MOP indicators,
- to evaluate the applicability of the MmGA to undertake real-world MOPs, and
- to hybrid EA models and other neural computing models in forming new MOEA models.
Thank You

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