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

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Research Review
Modified micro Genetic Algorithm-based Models 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).

An example of the typical cost-profit trade-off and the Pareto front.

**Pareto non-dominated solutions:**
An optimisation phenomenon whereby, given a set of solutions, it is impossible to improve one solution without degrading one or more other solutions.
Why using **Evolutionary Algorithm** (EA)?

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

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

![Diagram showing indicators for measuring convergence and diversity](image-url)
This research focuses on tackling MOPs using MOEA-based models.

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

- 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 model is evaluated comprehensively using benchmark MOPs
The key research question 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 aim is:

- to improve the original mGA model in tackling MOPs with good convergence properties towards the Pareto front
### 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 (Frutos 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>
The population sizes in mGA-based models

- **SOP**
  - Size 5: Krishnakumar (1990), Johnson and Abushagur (1995), Smajic et al. (2009), Watanabe et al. (2010), Itoh et al. (2012)
  - Size 6: Chu et al. (2013)
  - Size 7: Ali and Ramaswamy (2009)
  - Size 3, 5: Mendoza et al. (2007)

- **MOP**
  - Size 5: Mendoza et al. (2009)
  - Size 6: Chen (2011)
The pseudo-code of the MmGA model

```
Require: Generate non-dominated solutions for MOP

Procedure MmGA
    \( m = Sort(m_{init}, \leq) \) \( \triangleright O(N) \)
    \( p_{init} = Initialise\text{Population}(n, ratio, irm, rm, m) \) \( \triangleright O(c_0 \times N^2) \)
    \( p = Sort(p_{init}, \leq) \) \( \triangleright O(c_0 \times N) \)
    while \( i < \text{evaluationMax} \) do
        \( u = \text{Binary tournament selection on } p \) \( \triangleright O(c_0 \times c_1 \times MN^2) \)
        \( v = \text{Two-Point crossover on } u \)
        \( w = \text{Uniform mutation on } v \)
        \( p_{MmGA} = ^*\text{MmGAElitism}(w, p, 1) \)
        Produce the next generation
    until \( \text{nominalConvergence}_{\text{Max}} \) is reached

\( \text{em}_{\text{MmGA}} = ^*1\text{MmGAElitism}(p_{MmGA}, em, eliteSize) \) \( \triangleright O(c_0 \times MN^2) \)

if \( \text{em} \) is full when trying to insert \( \text{em}_{\text{elite}} \) then
    \( \text{em} = \text{adaptiveGrid}(\text{em}_{\text{elite}}) \) \( \triangleright O(\text{eliteSize} \times c_0 \times N) \)
end if

\( m = ^*2\text{MmGAElitism}(p_{MmGA}, m, eliteSize) \) \( \triangleright O(c_0 \times MN^2) \)

if \( i \) modulus replacementCycle then
    \( rm = ^*3\text{MmGAElitism}(em, rm, eliteSize) \) \( \triangleright O(c_0 \times MN^2) \)
end if

end while

return \( p_{MmGA} \) \( \triangleright \) * the modification compare to mGA

\( ^*1, ^*2, ^*3 \) are first, second and third form of elitism mGA, respectively
```

- Improving the convergence properties towards the true Pareto front as compared with mGA using
  - An NSGAII inspired elitism method
  - An extended population formation method
Key result: It achieved fast convergence with statistically better performance (at the 95% confidence level)

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 MmGA Model
A Case Study of Multi-objective Job-Shop Scheduling at Australia

Key result: The requirements are satisfied within a fraction of the time with statistical significance results.

<table>
<thead>
<tr>
<th>Jobs</th>
<th>Ψ (dollar)</th>
<th>Γ (day)</th>
<th>Time (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>4.5 to 5.16</td>
<td>5.0 to 6.0</td>
<td>&gt; 1000</td>
</tr>
<tr>
<td>6</td>
<td>11.09 to 14.87</td>
<td>21.0 to 12.0</td>
<td>&gt; 1000</td>
</tr>
<tr>
<td>7</td>
<td>13.68 to 14.49</td>
<td>30.0 to 17.0</td>
<td>&gt; 1000</td>
</tr>
<tr>
<td>8</td>
<td>17.5 to 19.06</td>
<td>31.0 to 26.0</td>
<td>&gt; 1000</td>
</tr>
<tr>
<td>10</td>
<td>13.4 to 16.77</td>
<td>13.0 to 0.0</td>
<td>&gt; 1000</td>
</tr>
</tbody>
</table>

A comparison of Cost-Saving (Ψ) and Tardiness (Γ) with the enumeration method ²

**Key result:** The stability of the average results is ascertained by the estimated 95% confidence intervals, which meet the requirements of the electronic engineer.

A comparison of voltage gain, cutoff frequency and passband ripple results between the MmGA model and the baseline requirement.

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The MmGA Ensemble Model

A schematic diagram of the MmGA Ensemble model.

To form an ensemble structure, multiple MmGA models are grouped together with a decision combination module.
The MmGA Ensemble Model

- Further improving the convergence properties towards the true Pareto front as compared with MmGA using
  - a voting-based elite selection scheme
  - an Apportionment of Credit (AoC) scheme for the rm (replacement memory) component of MmGA
  - a Reinforcement Learning (RL) scheme for the rm component
  - an RL scheme for the adoption ratio of the rm component
  - an Euclidean distance scheme for the final rm component replacement
Classifier fusion concept has been used to form a group of MmGA optimizers.

Their chromosomes represent the optimal search strings of the feature subsets.

To approximate the Pareto optimal solutions with the consideration of trade-offs in three objectives, i.e., maximizing specificity and sensitivity as well as minimizing the number of features.
**Key result:** It produced statistically better accuracy rates with fewer number of features (at the 95% confidence level).

A comparison of the Accuracy rate between the standard classifiers and the MmGA Ensemble coupled with the similar set of classifiers.  

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Key result: It produced 50% reduction in the number of features (i.e., 1560 from 3114) with 3% reduction in accuracy.

<table>
<thead>
<tr>
<th></th>
<th>Accuracy (%)</th>
<th>No. of features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronics to Electronics</td>
<td>85.9%</td>
<td>1560</td>
</tr>
<tr>
<td>Kitchen Appliances to Kitchen Appliances</td>
<td>88.0%</td>
<td>1559</td>
</tr>
<tr>
<td>Electronics to Kitchen Appliances</td>
<td>82.3%</td>
<td>1560</td>
</tr>
<tr>
<td>Kitchen appliances to Electronics</td>
<td>83.0%</td>
<td>1560</td>
</tr>
</tbody>
</table>

A comparison of In-domain and cross-domain results between the SVM classifier and the MmGA Ensemble 5

The key contributions of this research are as follows:

- Created Modified mGA(MmGA)-based models to provide near optimal solutions with reference to the true Pareto front for undertaking MOPs
- Assessed the proposed models with benchmark MOPs
- Conducted a comprehensive performance comparison with other similar models
- Evaluated the usefulness of MmGA-based models in solving real-world MOPs
Future Works

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-based models to undertake more real-world MOPs, and
- to hybrid EA models and other neural computing models in forming new MOEA models.
Thank You

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