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

Research Review

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

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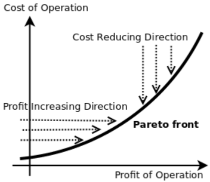
Real-world problems often entail multiple and yet conflicting objectives, known as **Multi-objective Optimization Problems** (MOPs)



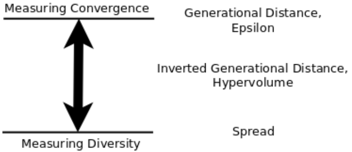
An example of the typical cost-profit trade-off and the Pareto front.

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

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

- EAs are useful for tacking 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) evolutes 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

Preliminaries

Research Focus

- 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

MOEA Category	Usage
Decomposition-based	Novel MOEA design and formation (Li and Zhang, 2009; Ke et al., 2013), and arc routing problem (Mei et al., 2011a).
Preference-based	Novel MOEA design and formation (Thiele et al., 2009; Liu, Wang, Liu, Fang and Jiao, 2013; Wagner and Trautmann, 2010).
Indicator-based	Novel MOEA design and formation (Wagner and Trautmann, 2010; Bader and Zitzler, 2011), and nurse scheduling (Basseur et al., 2012).
Hybrid-based	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 salesperson problem (Castro et al., 2013).
Memetic-based	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).
Co-evolution-based	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).

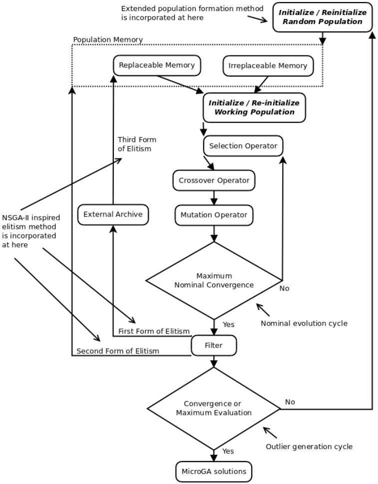
Literature Review
mGA-based models

Year	Model	Characteristics and Usage
2001, 2005	mGA (Coello and Pulido, 2001, 2005)	Original mGA implementation for undertaking benchmark MOPs.
2003	mGA2 with an adaptive parameter tuning mechanism (Toscano Pulido and Coello, 2003)	An extended mGA (Coello and Pulido, 2001) for undertaking benchmark MOPs.
2007	mGA with Newton-Raphson load flow algorithm (Mendoza et al., 2007)	A model used to optimize localization of AVRs.
2009	mGA with novel encoding and genetic operators (Mendoza et al., 2009)	A model used to optimize power losses and reliability indices in a power distribution system.
2011	mGA with a fuzzy controller (Chen, 2011)	A model used to optimize parameters of a fuzzy controller for vehicle suspension control design.

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)
- MOP
  - Size 3, 5: Mendoza et al. (2007)
  - Size 4: Coello and Pulido (2001); Coello and Toscano Pulido (2001); Coello and Pulido (2005), Toscano Pulido and Coello (2003)
  - Size 5: Mendoza et al. (2009)
  - Size 6: Chen (2011)

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 $\mathbf{x}^t$ where maximum $|\mathbf{x}^t| = 2N$, $|\mathbf{y}| \rightarrow$ constant c_1

Procedure MmGAElitism ($\mathbf{x}^t$, $\mathbf{y}$, c_0)
$\mathbf{z} = \{\neg(\mathbf{x}^t \cap \mathbf{y}) \mid \mathbf{z} \in \mathbf{x}^t\}$
$\mathbf{w} = \text{FNDS}(\mathbf{z})$ /**adopted from (Deb et al., 2002)**/
$i = 1$
while $i \leq (2N + c_1)$ **do**
  CDAssignment(w_i) /**adopted from (Deb et al., 2002)**/
  $i = i + 1$
end while
$\mathbf{e} = Sort(\mathbf{w}, \preceq_{CD})$ /** adopted from (Deb et al., 2002)**/
return $\{\mathbf{e} \mid \forall \mathbf{e} \in \neg(\mathbf{x}^t \cap \mathbf{y}) \cup \mathbf{y}, |\mathbf{e}| = c_0 + c_1\}$

An NSGA-II inspired elitism strategy.

The MmGA Model

Require: Generate constant n number of populations based on given inbound and constant c_0 members' adoption rate
Procedure InitializePopulation (n, c_0, **irm**, **rm**, **m**)
$\mathbf{p}_{init} = \mathbf{irm}$
$\mathbf{r} = \{[r_1,\ldots,r_n] \mid \forall \mathbf{r} \in \text{random}(\mathbb{N}), \mathbb{N} = [1,2,\ldots], r_k \leq n\}$
$\mathbf{d} = [\mathbf{rm}, \mathbf{m}]$
$i = 1$
while $i \leq |\mathbf{d}|$ **do**
$z_{unique} = \{\neg(d_i \cap \mathbf{p}_{init}), |\mathbf{p}_{init}| \leq n, \forall z_{unique} \in d_i, |z_{unique}| \leq d_i\}$
$z_{sorted} = \{Sort(z_{unique}, \preceq)\}$
if $i = 1$ **then** /**for **rm** component**/
$c_1 = c_0 \times (n - |\mathbf{irm}|)$
*Add c_1 members from z_{sorted} to $\mathbf{p}_{init}$
end if
if $i = 2$ **then** /**for **m** component**/
$c_1 = \{c_0 \times (n - |\mathbf{p}_{init}|), |\mathbf{p}_{init}| \neq 0, c_0 > 0\}$
for $j = 1 \to c_1$ **do**
*Add (r_j)th of z_{sorted} to $\mathbf{p}_{init}$
end for
end if
$i = i + 1$
end while
if $|\mathbf{p}_{init}| \leq n$ **then** /**for new random elements**/
$c_1 = \{n - |\mathbf{p}_{init}|, |\mathbf{p}_{init}| \neq 0, c_0 > 0\}$
for $j = 1 \to c_1$ **do**
*Add random solution to $\mathbf{p}_{init}$
end for
end if
return $\mathbf{p}_{init}$

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

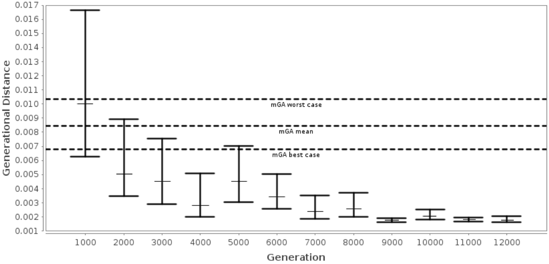
The MmGA Model

Require: Generate non-dominated solutions for MOP

Procedure MmGA
  $i = 0, \mathbf{p}_{MmGA} = \phi$
  $\mathbf{em} = f(archiveSize, BiSection, n) = \phi$
  Initialize $\mathbf{m}_{init}$
  $\dagger\mathbf{m} = Sort(\mathbf{m}_{init}, \preceq)$
  while $i < evaluation_{Max}$ **do**
    $\dagger\mathbf{p}_{init} = InitializePopulation(n, ratio, \mathbf{irm}, \mathbf{rm}, \mathbf{m})$
    $\dagger\mathbf{p} = Sort(\mathbf{p}_{init}, \preceq)$
    repeat
      $\mathbf{u}$ = Apply binary tournament selection on $\mathbf{p}$
      $\mathbf{v}$ = Apply two-Point crossover on $\mathbf{u}$
      $\mathbf{w}$ = Apply uniform mutation on $\mathbf{v}$
      $p_i^{MmGA} = \dagger MmGAElitism(\mathbf{w}, \mathbf{p}, 1)$
    until $nominalConvergence_{Max}$ is reached
    $\mathbf{em}_{MmGA} = \dagger^1 MmGAElitism(\mathbf{p}_i^{MmGA}, \mathbf{em}, eliteSize)$
    if $\mathbf{em}$ is full when trying to insert $\mathbf{em}_{elite}$ **then**
      $\mathbf{em} = adaptiveGrid(\mathbf{em}_{elite})$ /**adopted from (Knowles and Corne, 2000)**/
    end if
    $\mathbf{m} = \dagger^2 MmGAElitism(\mathbf{p}_i^{MmGA}, \mathbf{m}, eliteSize)$
    if i modulus $replacementCycle$ **then**
      $\mathbf{rm} = \dagger^3 MmGAElitism(\mathbf{em}, \mathbf{rm}, eliteSize)$
    end if
    $i = i + 1$
  end while
  return $\mathbf{p}^{MmGA}$
    /**$\dagger^1, \dagger^2, \dagger^3$ are the first, second and third forms of elitism mGA, respectively.**/

The pseudo-code of the overall MmGA model.

Key result: It achieved fast convergence in I_{gd} with statistical significance results.



A comparison between I_{gd} of mGA (i.e. dotted lines) and bootstrapped I_{gd} of MmGA. The error bars indicate the 95% confidence intervals of the mean I_{gd} results of MmGA.

Conclusions and Contributions

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 details of this research is published: Tan, C. J., Lim, C. P. and Cheah, Y.-N. (2013). A modified micro genetic algorithm for undertaking multi-objective optimization problems, Journal of Intelligent and Fuzzy Systems 24(3): 483-495.

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 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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