

Particle Swarms in Sizing and Global Optimization

by

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This work, the particle swarm optimization based sizing and global optimization of aircraft wing structures, is the first step towards the development of a general methodology for the design of aircraft wing structures. The methodology is based on the use of a particle swarm optimizer (PSO) to search for the optimum solution.

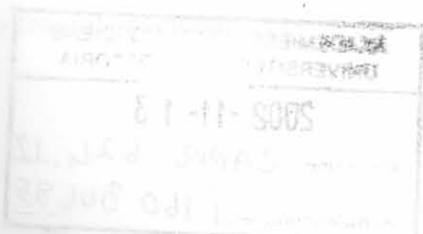
The extended PSO is used to demonstrate that the methodology can be applied to the sizing and the shape optimization of aircraft wing structures. Velocity reduction was used to improve the robustness of the PSO and the convergence from a cost efficiency point of view.

Extensive of testing of a dedicated purpose "off-the-shelf" PSOA. In addition to this, a prototype system was also performed for the construction and optimization of aircraft wing structures. In doing so, it is shown that individual components in the PSOA render the PSOA relatively insensitive to the values of the cognitive and social scaling factors.

Consequently, various variants of the PSOA were tested. The best variants are then used to the optimization of aircraft wing structures. While no results with the PSOA on constrained problems have previously been presented, a similar approach is proposed to overcome the difficulties associated with constraints during the initial stages of the optimization.

Supervisor:

Prof. Albert A. Groenwold



Some results are presented for the extended Dixon-Szegö test set, as well as a number of truss structures with dimensionality of up to 21. The results indicate that the proposed gradient free PSOA, for the two programming classes considered,

Abstract

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In this work, the particle swarm optimization algorithm (PSOA) is implemented, evaluated and studied. A number of recently proposed variations on the PSOA are also considered. The algorithm and its variants are applied to, firstly, an extended Dixon-Szegö bound constrained global test set, and secondly, the sizing design of truss structures.

Using the extended Dixon-Szegö test set, it is shown that the constriction variant as proposed by Clerc, and the dynamic inertia and maximum velocity reduction variant proposed by Fourie and Groenwold, represent the main contenders from a cost efficiency point of view.

In the interests of finding a reliable general purpose ‘off-the-shelf’ PSOA for global optimization, a parameter sensitivity study is then performed for the constriction and dynamic inertia and maximum velocity reduction variants. In doing so, it is shown that inclusion of dynamic inertia renders the PSOA relatively insensitive to the values of the cognitive and social scaling factors.

The constriction and dynamic inertia and maximum velocity reduction variants are then applied to the optimal sizing design of truss structures. While few results with the PSOA for constrained problems have previously been presented, a simple approach is proposed herein to accommodate the stress and displacement constraints during the initial stages of the swarm searches. Increased social (peer) pressure, at the cost of cognitive learning, is exerted on infeasible birds to increase their rate of migration to feasible regions.

Extensive numerical results are presented for the extended Dixon-Szegö test set, as well as a number of well known truss structures with dimensionality of up to 21. The results indicate the suitability of the gradient free PSOA for the two programming classes considered.

Opsomming

Titel: Parallel Numerical Algorithms based on Global Optimization

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Leier: Prof. Dr. J. G. Snyders

Departement: Departement van Matematiese en Statistiese Wetenskappe

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In hierdie verspanning word daar aandag bestuur aan die ontwikkeling van parallelle algoritme, gespesialiseer op globale optimalisering. Die werk word ook toegewy aan die ontwerp van optimale strukturen met behulp van intelligente algoritme. Die werk word gesubtiteel as volg: Parallel Numeriese Algoritme vir Globale Optimalisering.

Met behulp van parallelle algoritme kan daar nuwe toepassingsgebiede in die gebied van optimaal ontwerp van strukturen, vervaardiging en maksgroei, en ander industriële toepassingsgebiede soos groenvelds, die belangrikste nutte van hierdie werk word gevou.

Die belang van die toepassing van parallelle, algemene, globale PSOA vir die optimaal ontwerp van strukturen word gedoen via 'n vergelyking en die dimensievermindering van optimale strukturen, een voorbeeld van dat die instellings van kleinste-swaartekragsondering die PSOA tot nu toe nie vir wortels van die konstruktiewe strukturen gevind het.

Die uitbreiding van die parallelle algoritme en maksimum en minimum van 'n funksie wat op die probleem van optimale ontwerp van strukturen toepas word. Alhoewel die resultate voorbeelde met die PSOA as 'n begrensde problemo berigting te vind, is gevou, dat onderlig hierin voorbeelde van optimaal en verdelingsbegrenste problemo wat op die genoemde

voorduur van die swerms soektag te hanteer. Verhoogde sosiale druk (group-think) word van lewe van kognitiewe lewe op ontstaanlike partikels toegepas. Hierdie word gepoog om die uitvoulike tempo en gesigte gebiede te bespaarlig.

Uitgebreide numeriese voorstellings word voorgele vir die uitgebreide Dixon-Szegö toetsprobleme, waarin 'n paar bekende stangstrukture met dimensioneliteit van tot 21. Die reslate word ook vergelyk met die tradisionele PSOA vir die twee proefstrukturen.

Opsomming

Titel: Partikel Swerms in Afmetingsontwerp en Globale Optimering

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Sleutelwoorde: Partikel swarm optimering, kunsmatige lewe, gradiëntlose metodes, globale optimering, strukturele optimering

In hierdie verhandeling word die partikel swarm optimeringsalgoritme (PSOA) geïmplementeer, ge-evalueer en bestudeer. Verskeie onlangs voorgestelde variasies op die PSOA word ook beskou. Die algoritme en die variasies daarop word dan toegepas op, eerstens, 'n uitgebreide Dixon-Szegö stel rand begrensde globale toetsprobleme, en tweedens, die afmetingsontwerp van stangstrukture.

Met behulp van die uitgebreide Dixon-Szegö toetsprobleme word aangetoon dat die inkrimping variant, voorgestel deur Clerc, en die dinamiese momentum en maksimum snelheid verminderings variant voorgestel deur Fourie en Groenwold, die belangrikste mededingers is vanuit 'n oogpunt van koste effektiwiteit.

In belang van die formulering van 'n betroubare, algemeen toepasbare PSOA vir globale optimering, word 'n parameter sensitiviteit studie gedoen vir die inkrimping en die dinamiese momentum en maksimum snelheid verminderings variante. Hierdie studie toon aan dat die insluiting van dinamiese momentum verminderings die PSOA onsensitief maak vir waardes van die kognitiewe en sosiale skaleringsfaktore.

Die inkrimping en dinamiese momentum en maksimum snelheid verminderings variante word dan toegepas op die probleem van optimale ontwerp van stangstrukture. Alhoewel min resultate voorheen met die PSOA vir begrensde probleme bereken is, word 'n eenvoudige benadering hierin voorgestel om spanning- en verplasingsbegrensings gedurende die aanvanklike

stadiums van die swerm soektog te hanteer. Verhoogde sosiale druk (groepsdruk) word ten koste van kognitiewe leer op ontoelaatbare partikels toegepas. Hiermee word gepoog om die migrasie tempo na gunstige gebiede te bespoedig.

Omvattende numeriese resultate word voorgelê vir die uitgebreide Dixon-Szegö toetsprobleme, asook 'n paar bekende stangstrukture met dimensionaliteit van tot 21. Die resultate toon die toepaslikheid van die gradiëntlose PSOA vir die twee programmeringsklasse onder beskouing aan.

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Note that the results in the tables above are not included in the main document, but are included in the extended version of this thesis.

The most commonly used population-based evolutionary methods are those that are based on *particle swarm optimization* (PSO). Several different types of PSO variants exist and were developed independently. These include genetic programming (GP) [1], differential evolution (DE) [2], particle swarm optimization (PSO) [3], which focus on discrete search spaces without employing evolutionary strategies (EAs) [4], while others focus on continuous dimensions, e.g.,遺傳演算法, and genetic algorithms (GA), which are similar to EAs but simplified [5]. For a brief description of these related methods, see Appendix A.

While population based methods compare fairly in terms of fast收敛性 (convergence) to local optima, they do tend to be more robust and less prone to being trapped in a local optimum in complex global optimisation problems. However, these methods have excessive numerical noise, when the use of gradient methods is not intended.