

Constriction

Figure 3.10(a) indicates that the optimum cognitive value for the extended Dixon-Szegö test set tends to be in the region between 1.5 and 2, indicating that the recommended setting of 2.8 by Carlisle and Dozier is also appropriate for the problems in the extended Dixon-Szegö test set, but considering cost. Figure 3.10(b) shows the optimum value for reliability remains constant at 2.8 values in the region of 1.5. The Griewank C2 problem however shows a sharp decrease in reliability for values of  $c_1$  of 3 or 3. Again, a value of 2.8 would probably be a suitable compromise to ensure good reliability.

## Chapter 5

# Parameter sensitivity analysis

Dynamic inertia reduction and maximum velocity limitation

Results with PSO: The PSO algorithm with dynamic inertia reduction and maximum velocity limitation

### 5.1 Overview

In this chapter the two most promising variants of the PSO, namely the constriction method of Clerc and the dynamic inertia and maximum velocity reduction method of Fourie and Groenwold, are subjected to a parameter sensitivity analysis. The main objective of this study is to ascertain what parameter values will result in a general purpose algorithm which will perform well for the entire test set.

#### 5.1.1 Cognitive/social ratio

While it is noted that linear inertia reduction yields good reliability, the results presented in Section 4.4 indicate that constriction and the dynamic inertia/velocity reduction variants are the main contenders when both reliability and cost are considered. Choosing between these two contenders seems difficult, and should probably be judged in future on problems with higher dimensionality than considered herein.

Previously, Kennedy asserted that the sum of the cognitive and social values  $c_1$  and  $c_2$  should approximately equal 4.0, [13], if the cognitive and social ratio is adjusted in the constriction factor method. Carlisle and Dozier [20] have shown that it is advantageous to adjust the cognitive/social ratio to favor cognitive learning (an individualistic swarm). They report that values of 2.8 and 1.3 respectively for the cognitive and social components yield the best performance for the test set they consider.

In the following subsections, it is investigated whether this is true for the extended Dixon-Szegö test set under consideration. Numerical results presented in Figures A.10(a), A.10(b), A.11(a), A.11(b) are obtained by varying the cognitive value  $c_1$  between 0 and 4.1, with the social value calculated in each case as  $c_2 = 4.1 - c_1$ , as suggested by Carlisle and Dozier [20].

## Constriction

Figure A.10(a) indicates that the optimum cognitive value for the extended Dixon-Szegö test set tends to be in the region between 1.5 and 3, indicating that the recommended setting of 2.8 by Carlisle and Dozier is also appropriate for the problems in the extended Dixon-Szegö test set when considering cost. Figure A.10(b) shows the optimum value for reliability to reveal a greater problem dependency, with graphs of the Hartman and Shekel family of problems peaking at  $c_1$  values in the region of 3.5. The Griewank G2 problem however shows a sharp decrease in reliability for values of  $c_1$  above 3. Again, a value of 2.8 would probably be a realistic compromise to ensure reasonable reliability.

## Dynamic inertia reduction and maximum velocity limitation

Results with dynamic inertia reduction and maximum velocity limitation (Figure A.11) indicates that this variant of the PSOA is relatively insensitive to the cognitive/social ratio. The cost remains low throughout the range of variation of the  $c_1$  parameter, with the sharp increase to 30000 function evaluations at values above 3.8, indicating that none of the iterations converged. The reliability is also relatively insensitive to the cognitive parameter  $c_1$  for the majority of the problems, with a drop in reliability at values above 3. The insensitivity to low values of cognitive learning indicates the successfulness of the purely 'social' swarm (e.g. see [12]). A reasonable value for this variant is 2.0, which was initially suggested by Kennedy and Eberhart [9] for the 'standard' PSOA.

To further investigate the sensitivity to cognitive/social ratio, the study is repeated, but with  $c_1 = c_2$  (Figure A.12). The results again indicate a relatively low sensitivity, with only the Griewank G2 and Shekel problems revealing a slight increase in cost for  $c_1 = c_2 > 2$ .

### 5.1.2 Swarm population size

The effect of swarm population size on constriction has been extensively studied by Carlisle and Dozier [20], Eberhart and Shi [32], and Shi and Eberhart [16].

For constriction, our findings closely supports the findings of Carlisle and Dozier, who maintain that, while an increase in population tends to lessen the required swarm *iterations*, the accompanying *cost* ( $N_{fe}$ ) increases. This is reflected in Figure A.13. Although populations of as little as 5 particles find the optimum at low cost, the sharp decrease in reliability with small population sizes dictate a lower bound when reliability is considered. A swarm population of 20-30 seems a reasonable compromise between cost and reliability.

For dynamic inertia reduction, very similar results to those of constriction are obtained (Figure A.14). A swarm size of 20 seems sufficient as a threshold value to prevent reduced reliability at the low end of the graph, while retaining reasonable cost.

### 5.1.3 Dynamic delay period and reduction parameters

The effect of the dynamic delay period  $h$  on the cost and reliability is depicted in Figure A.15. Both cost and reliability are quite insensitive to the value of  $h$ . The only exception to this is the Griewank G2 problem, which reveals a reduction in reliability for values of  $h$  above 10.

The effect of the reduction parameters  $\alpha$  and  $\beta$  in (3.5) are studied in Figure A.16. For the sake of simplicity,  $0.95 \leq \alpha = \beta \leq 1$  is selected. The study reveals a rapid increase in cost for  $\alpha = \beta > 0.99$  (Figure A.16(a)), since the algorithm approximates the constant inertia variant as  $\alpha, \beta$  approach 1. For values of  $\alpha = \beta < 0.99$ , the reliability decreases sharply (Figure A.16(b)), suggesting an optimal value of 0.99 for the extended Dixon-Szegö test set.

### 5.1.4 Initial velocity fraction

Dynamic inertia reduction is rather insensitive to the value of the initial velocity fraction  $\gamma$  (Figure A.17), although the reliability decreases sharply below  $\gamma = 0.3$ . A practical setting would probably be  $\gamma = 0.5$ .

## 5.2 Recommendations

It is proposed that either the constriction or the dynamic inertia reduction variants of the PSOA are used in global optimization. For constriction, the previously proposed values of  $c_1 = 2.8$  and  $c_2 = 1.3$  are supported. For dynamic inertia reduction, it is proposed that  $c_1 = c_2 = 2.0$ ,  $h = 10$ , and  $\alpha = \beta = 0.99$ . As far as swarm population size is concerned, both variations scale well, with a population size of 20 particles being optimal.

## 5.3 Summary

The PSOA and some of its variants have been applied to an extended Dixon-Szegö test set in global optimization. It is shown that constriction and dynamic inertia reduction are the main contenders when considering both reliability and cost.

For problems of low dimensionality, dynamic inertia reduction is marginally outperformed by constriction. For problems of higher dimensionality, dynamic inertia reduction seems slightly superior.

Dynamic inertia reduction is shown to be less sensitive to parameter variations than constriction, for which the optimum choice of cognitive  $c_1$  and social  $c_2$  scaling parameters tends to be problem dependent.