CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

In this work, a methodology to adapt the control parameters of Differential Evolution based on the diversity of the population is presented. The adaptation is implemented using a Fuzzy System (FS) to control the population diversity during the various phases of evolution through controlled parameter adaptation. The proposed diversity control based parameter adaptation is applied to vary the control parameters of Self adaptive Differential evolution (SaDE) algorithm. The methodology also includes a local search to provide balanced exploration and exploitation. Two algorithms namely Diversity Controlled SaDE with local search (DCSaDE-LS) with only $CR$ adaptation and Diversity Controlled Parameter adapted DE with Local Search (DCPaDE-LS) with both $CR$ and $F$ adaptation are proposed.

In order to demonstrate the effectiveness of diversity control and local search statistical results of SR, MF and NFE on a set of 26 standard benchmark functions are considered for a comparative study. Of these $f_1-f_{14}$ are scalable and 10, 30 and 50 dimensions are considered. Of the two algorithms, the DCPaDE-LS algorithm performs better in terms of SR and NFE for most of the functions.

In order to solve complex multimodal problems within limited computational budget, surrogate models are integrated with EA. In this work
the better performing DCPaDE-LS algorithm is dynamically integrated with two surrogate models namely Artificial Neural Networks (ANN) and Response Surface Methodology (RSM) to reduce the exact function evaluations for complex, multimodal problems. The performance of the proposed Surrogate Assisted Parameter adapted DE (SAPDE) variants are compared on the same set of 26 bound-constrained benchmark functions with 10D and 30D functions.

The DCSaDE-LS algorithm is compared with two variants namely the DCSaDE and SaDE-LS algorithms and the SaDE algorithm on the 26 benchmark function with 10D and 30D dimension functions. It is clear from the results obtained, that applying diversity control alone (DCSaDE) generally requires more function evaluations and in some cases SR is decreased. The SaDE-LS algorithm requires comparatively lesser NFEs as compared to the SaDE, but SR is not consistent. Specifically, DCSaDE-LS algorithm gives improved performance in SR for 30D multimodal functions. There are savings also in NFEs without any SR deterioration. Only with the combined effect of a diversity control and a local search (DCSaDE-LS), better performance can be achieved.

The DCPaDE-LS algorithm is compared with SaDE, SaDE-LS and DCSaDE-LS algorithms. The performance of the algorithms are compared on the benchmark functions 10D, 30D and 50D variants. DCPaDE-LS algorithm gives savings in terms of NFE for most of the 10D functions. The algorithm also, shows improvement in terms of SR as well as NFE for 30D functions. In the 50D functions group, DCPaDE-LS algorithm distinctly outperforms the other two algorithms in all the three measures MF, SR, and NFE.
The DCSaDE-LS and DCPaDE-LS algorithms are compared with G-CMAES, CLPSO and RGA algorithms. Both the algorithms perform significantly better than CLPSO and RGA in all the type of problems. G-CMAES performs better in few multimodal problems where all the other algorithms fail. But the SR decreases for an equal number of multimodal problems. G-CMAES also reports varying performance in terms of SR for 30D and 50D functions as compared to DCPaDE-LS algorithm. Three nonparametric statistical tests have also been applied to validate the results. It is proved through these analyses that DCSaDE-LS algorithm performs better than others in 10D and 30D problems with a significance level of 0.05. Nonparametric statistical tests to validate the DCPaDE-LS algorithm are applied for 30D and 50D functions and it outperforms the other algorithms with a 0.05 significance level. G-CMAES performs the best for problems \( f_{15} - f_{26} \), but it is not significantly better than DCSaDE-LS and DCPaDE-LS algorithms. This methodology can be easily applied to other evolutionary algorithms by suitably modifying the FS.

The performances of the proposed two SAPDE variants are compared with DCPaDE-LS algorithm on the benchmark functions with 10D and 30D variants. The simulation results show that SAPDE variants reports significant reduction in NFE for the same SR. SAPDE-ANN is able to give better performance in terms of reduction in NFE in more functions as compared to SAPDE-RSM. The proposed SAPDE algorithms can be applied to real world multimodal optimization problems for reducing computational burden without compromising on performance.

6.2 SCOPE FOR FUTURE WORK

The proposed DCSaDE-LS and DCPaDE-LS algorithms can be applied to solve:
Large scale global optimization problems listed in CEC 2010 (Tang et al 2009)

Constrained benchmark real parameter optimization problems listed in CEC 2010 (Mallipeddi and Suganthan 2010).

Constrained real world optimization problems listed in CEC 2011 (Das and Suganthan 2010).

Many real world optimization problems like control system optimization (Maruta et al 2009), optimization problems in bioinformatics (Bajaj et al 2011) etc.

The scope for further research work in SAPDE algorithms includes,

- Various other surrogate models like Support Vector machine (SVM), Extreme Learning Machine (ELM) etc. can be integrated for better performance.

- The integration methodology can be further improved to increase the accuracy without substantial increase in function evaluations.

- Design optimization problems in real world without loss of accuracy (Emmerich et al 2006, Buckley et al 2010).