

**IMPROVING ROBUSTNESS IN SOCIAL FABRIC-BASED
CULTURAL ALGORITHMS**

By

Bahram Zaeri

A Thesis

Submitted to the Faculty of Graduate Studies
Through the School of Computer Science

In Partial Fulfillment of the Requirements for
the Degree of Master of Science at the

University of Windsor

Windsor, Ontario, Canada

2017

© Bahram Zaeri, 2017

Improving Robustness in Social Fabric-based Cultural Algorithms

by

Bahram Zaeri

APPROVED BY:

Supervisory Committee

Dr. Kemal Tepe, External Reader

(Department of Electrical and Computer Engineering)

Dr. Mehdi Kargar, Internal Reader

(School of Computer Science)

Dr. Ziad Kobti, Advisor

(School of Computer Science)

DECLARATION OF ORIGINALITY

I at this moment certify that I am the sole author of this thesis and that no part of this thesis has been published or submitted for publication.

I certify that, to the best of my knowledge, my thesis does not infringe upon anyone's copyright nor violate any proprietary rights and that any ideas, techniques, quotations, or any other material from the work of other people included in my thesis, published or otherwise, are fully acknowledged in accordance with the standard referencing practices. Furthermore, to the extent that I have included copyrighted material that surpasses the bounds of fair dealing within the meaning of the Canada Copyright

Act, I certify that I have obtained a written permission from the copyright owner(s) to include such material(s) in my thesis and have included copies of such copyright clearances to my appendix.

I declare that this is a true copy of my thesis, including any final revisions, as approved by my thesis committee and the Graduate Studies office, and that this thesis has not been submitted for a higher degree to any other University or Institution.

ABSTRACT

In this thesis, we propose two new approaches which aim at improving robustness in social fabric-based cultural algorithms. Robustness is one of the most significant issues when designing evolutionary algorithms. These algorithms should be capable of adapting themselves to various search landscapes.

In the first proposed approach, we utilize the dynamics of social interactions in solving complex and multi-modal problems. In the literature of Cultural Algorithms, Social fabric has been suggested as a new method to use social phenomena to improve the search process of CAs. In this research, we introduce the Irregular Neighborhood Restructuring as a new adaptive method to allow individuals to rearrange their neighborhoods to avoid local optima or stagnation during the search process.

In the second approach, we apply the concept of Confidence Interval from Inferential Statistics to improve the performance of knowledge sources in the Belief Space. This approach aims at improving the robustness and accuracy of the normative knowledge source. It is supposed to be more stable against sudden changes in the values of incoming solutions.

The IEEE-CEC2015 benchmark optimization functions are used to evaluate our proposed methods against standard versions of CA and Social Fabric. IEEE-CEC2015 is a set of 15 multi-modal and hybrid functions which are used as a standard benchmark to evaluate optimization algorithms. We observed that both of the proposed approaches produce promising results on the majority of benchmark functions. Finally, we state that our proposed strategies enhance the robustness of the social fabric-based CAs against challenges such as multi-modality, copious local optima, and diverse landscapes.

DEDICATION

To my loving family:

Mother: Marzieh Taghavi

Brother: Brhnam Zaeri

Sister: Sheida Zaeri

Sister: Narges Zaeri

ACKNOWLEDGEMENTS

I would like to express the deepest appreciation to my supervisor Dr. Ziad Kobti, who has the attitude and the substance of a genius: he continually and convincingly conveyed a spirit of adventure regarding research and scholarship and excitement with teaching. Without his guidance and persistent help, this thesis would not have been possible.

I would like to thank my committee members, Dr. Mehdi Kargar and Dr. Kemal Tepe as the internal and external readers respectively for their support and positive attitude towards my research work.

I appreciate Mrs. Gloria Mensah, the secretary of the director and Mrs. Karen Bourdeau, the graduate secretary for their help and support whenever I needed any assistance in academic issues.

Finally, I would like to thank my family and friends for their unconditional support in every step of my life.

Contents

DECLARATION OF ORIGINALITY	iii
ABSTRACT	iv
DEDICATION	v
ACKNOWLEDGEMENTS	vi
LIST OF TABLES	xi
LIST OF FIGURES	xiii
LIST OF ABBREVIATIONS/SYMBOLS	xv
1 Introduction	1
1.1 Evolutionary Algorithms	1
1.2 Robustness in Evolutionary Algorithms	2
1.3 Research Motivation	3
1.4 Thesis Contribution	3
1.5 Thesis Outline	4
2 Related Works	6
2.1 Cultural Algoithms	6
2.1.1 Heterogeneous Multi-Population Cultural Algorithm	6

2.1.2	The Social Fabric Approach as an Approach to Knowledge Integration in Cultural Algorithms	8
2.1.3	Robust Evolution Optimization at the Edge of Chaos: Commercialization of Culture Algorithms	10
2.1.4	Socio-Cultural Evolution via Neighborhood-Restructuring in Intricate Multi-Layered Networks	11
2.1.5	Leveraged Neighborhood Restructuring in Cultural Algorithms for Solving Real-World Numerical Optimization Problems	14
2.2	Particle Swar Optimization	16
2.2.1	Tribe-PSO: A novel global optimization algorithm and its application in molecular docking	16
2.2.2	Heterogeneous Particle Swarm Optimizers	17
2.3	Chapter Conclusion	19
3	Evolutionary Algorithms	20
3.1	Evolutionary Algorithms	20
3.2	Cultural Algorithms	22
3.2.1	Belief Space	22
3.2.2	Population Space	23
3.2.3	Communication Protocol	23
3.3	Social Fabric-based Cultural Algorithms	24
3.3.1	Evolution Phases	25
3.3.2	Strategic Neighborhood Restructuring	25
3.3.3	Social fabric based influence function	26
3.4	Particle Swarm Optimization	26
3.4.1	Tribe-PSO	28
3.5	Chapter Conclusion	29

4 Proposed Approaches: Improving Robustness in Social Fabric	30
4.1 Self-organization	31
4.2 Irregular Neighborhood Restructuring	32
4.3 Confidence based Normative Knowledge Source	34
5 Experimental Setup	35
5.1 Description	35
5.2 Benchmark Functions	36
5.2.1 Unimodal Functions	36
5.2.2 Simple Multimodal Functions	37
5.2.3 Hybrid Functions	39
5.2.4 Composite Functions	40
5.3 Parameters Settings	43
6 Evaluation, Analysis and Comparisons	44
6.1 Function 1: Bent Cigar Function	44
6.2 Function 2: Discus Function	46
6.3 Function 3: Weierstrass Function	48
6.4 Function 4: Modified Schwefel’s Function	49
6.5 Function 5: Katsuura Function	50
6.6 Function 6: HappyCat Function	52
6.7 Function 7: HGBat Function	54
6.8 Function 8: Griewank’s plus Rosenbrock’s Function	55
6.9 Function 9: Expanded Scaffer’s F6 Function	57
6.10 Function 10: Hybrid Function 1	58
6.11 Function 11: Hybrid Function 2	60
6.12 Function 12: Hybrid Function 3	61
6.13 Function 13: Composition Function 1	63

6.14 Function 14: Composition Function 2	64
6.15 Function 15: Composition Function 3	66
6.16 Summary of Results	67
7 Conclusion and Future Work	69
7.1 Conclusion	69
7.2 Future Work and Applications	70
Bibliography	72

List of Tables

Table 6.1	function-1, dimension-10	45
Table 6.2	function-1, dimension-30	45
Table 6.3	function-2, dimension-10	46
Table 6.4	function-2, dimension-30	47
Table 6.5	function-3, dimension-10	48
Table 6.6	function-3, dimension-30	48
Table 6.7	function-4, dimension-10	49
Table 6.8	function-4, dimension-30	49
Table 6.9	function-5, dimension-10	51
Table 6.10	function-5, dimension-30	52
Table 6.11	function-6, dimension-10	52
Table 6.12	function-6, dimension-30	53
Table 6.13	function-7, dimension-10	54
Table 6.14	function-7, dimension-30	54
Table 6.15	function-8, dimension-10	55
Table 6.16	function-8, dimension-30	56
Table 6.17	function-9, dimension-10	57
Table 6.18	function-9, dimension-30	57
Table 6.19	function-10, dimension-10	58
Table 6.20	function-10, dimension-30	59
Table 6.21	function-11, dimension-10	60

Table 6.22	function-11, dimension-30	60
Table 6.23	function-12, dimension-10	61
Table 6.24	function-12, dimension-30	62
Table 6.25	function-13, dimension-10	63
Table 6.26	function-13, dimension-30	64
Table 6.27	function-14, dimension-10	64
Table 6.28	function-14, dimension-30	65
Table 6.29	function-15, dimension-10	66
Table 6.30	function-15, dimension-30	66

List of Figures

Figure 2.1	H-MPCA Architecture [Raeesi and Kobti, 2013]	7
Figure 2.2	Scale of social interactions [Reynolds and Ali, 2008]	8
Figure 2.3	Multi-Layered Social Network with CA [Ali et al., 2012] . . .	12
Figure 2.4	Two-class taxonomy of the tribal CA [Ali et al., 2016]	15
Figure 3.1	Cultural Algorithms [Raeesi and Kobti, 2013]	24
Figure 3.2	Standard Neighborhood Restructuring Process	25
Figure 3.3	Social Fabric Influence Function[Ali and Reynolds, 2009] . . .	27
Figure 3.4	Social interaction model of PSO	28
Figure 3.5	Tribal-PSO	29
Figure 6.1	Average fitness values for Function 1 with 10 dimensions . . .	45
Figure 6.2	Average fitness values for Function 1 with 30 dimensions . . .	46
Figure 6.3	Average fitness values for Function 2 with 10 dimensions . . .	47
Figure 6.4	Average fitness values for Function 2 with 30 dimensions . . .	47
Figure 6.5	Average fitness values for Function 3 with 10 dimensions . . .	48
Figure 6.6	Average fitness values for Function 3 with 30 dimensions . . .	49
Figure 6.7	Average fitness values for Function 4 with 10 dimensions . . .	50
Figure 6.8	Average fitness values for Function 4 with 30 dimensions . . .	50
Figure 6.9	Average fitness values for Function 5 with 10 dimensions . . .	51
Figure 6.10	Average fitness values for Function 5 with 30 dimensions . . .	51
Figure 6.11	Average fitness values for Function 6 with 10 dimensions . . .	52
Figure 6.12	Average fitness values for Function 6 with 30 dimensions . . .	53

Figure 6.13 Average fitness values for Function 7 with 10 dimensions . . .	54
Figure 6.14 Average fitness values for Function 7 with 30 dimensions . . .	55
Figure 6.15 Average fitness values for Function 8 with 10 dimensions . . .	56
Figure 6.16 Average fitness values for Function 8 with 30 dimensions . . .	56
Figure 6.17 Average fitness values for Function 9 with 10 dimensions . . .	57
Figure 6.18 Average fitness values for Function 9 with 30 dimensions . . .	58
Figure 6.19 Average fitness values for Function 10 with 10 dimensions . . .	59
Figure 6.20 Average fitness values for Function 10 with 30 dimensions . . .	59
Figure 6.21 Average fitness values for Function 11 with 10 dimensions . . .	60
Figure 6.22 Average fitness values for Function 11 with 30 dimensions . . .	61
Figure 6.23 Average fitness values for Function 12 with 10 dimensions . . .	62
Figure 6.24 Average fitness values for Function 12 with 30 dimensions . . .	62
Figure 6.25 Average fitness values for Function 13 with 10 dimensions . . .	63
Figure 6.26 Average fitness values for Function 13 with 30 dimensions . . .	64
Figure 6.27 Average fitness values for Function 14 with 10 dimensions . . .	65
Figure 6.28 Average fitness values for Function 14 with 30 dimensions . . .	65
Figure 6.29 Average fitness values for Function 15 with 10 dimensions . . .	66
Figure 6.30 Average fitness values for Function 15 with 30 dimensions . . .	67

LIST OF ABBREVIATIONS/SYMBOLS

EA-Evolutionary Algorithms

CA-Cultural Algorithms

PSO-Particle Swarm Intelligence

EP-Evolutionary Programming

ACO-Ant Colony Optimization

H-MPCA: Heterogeneous Multi-Population Cultural Algorithm

MPCA-Multi-Population Cultural Algorithms

SF-Social Fabric

CI-Confidence Interval

RN-Neighborhood Restructuring

SFCA-Social Fabric-based Cultural Algorithms

ISFCA-Social Fabric-based Cultural Algorithms with Irregular Restructuring

ISFCA-Social Fabric-based Cultural Algorithms with Confidence Interval

Chapter 1

Introduction

1.1 Evolutionary Algorithms

Evolutionary algorithms take their roots from the evolution theory of Darwin. These algorithms try to mimic the collective behavior of natural systems. Natural processes such as natural selection, survival of the fittest, and reproduction have been subject to inspiration as the fundamental components of evolutionary problem-solving methods [Burke et al., 2005]. The basic part of all these algorithms is that they start with a randomly generated set of solutions. Then, they try to evolve the solutions through applying a set evolutionary operators such as mutation and crossover.

Evolutionary algorithms are not limited to biological processes. There is another category of evolutionary algorithms known as Swarm Intelligence (SI). These algorithms take inspiration from social behaviors of living colonies such as ants, flocks, schools, and hives [Kennedy et al., 2001]. Within these swarms, individuals have relatively simple structures, but their collective behavior usually looks very complicated. The complex behavior of a swarm emerges as a result of the interactions between the individuals over time. This complex behavior can not be easily predicted by observing the simple behaviors of the agents separately.

There are some well-known examples categorized as evolutionary algorithms:

1. Genetic Algorithms
2. Cultural Algorithms
3. Particle Swarm Optimization
4. Ant Colony Optimization
5. Honey Bee Colony

Both categories of evolutionary algorithms share the same idea of evolving some initially generated solutions. However, the difference is in the way that they manipulate and evolve individuals through applying evolutionary operators.

1.2 Robustness in Evolutionary Algorithms

In the evolutionary algorithms literature, robustness means that an algorithm can be used to solve many kinds of problems, with a minimum number of adjustments to address particular problems with particular qualities [Che et al., 2010]. Also, it can mean the capability of algorithms to deal acceptably with noisy or missing data [Kennedy et al., 2001]. Most of the optimization problems suffer from issues such as multi-modality and copious local optima. The most important defect that evolutionary algorithms face with is getting stuck in local optima. Evolutionary algorithms are expected to have enough flexibility (robustness) to detect the stagnation situations and deploy the strategies to get rid of them.

Swarm intelligence, as a state of the art evolutionary method, suggests the concept of self-organization improves robustness in population-based algorithms [Blum and Groß, 2015]. Self-organized algorithms are capable of coping with various search landscapes. They can learn and adapt themselves to different environments. So,

self-organized strategies allow the evolutionary algorithms to address a wide range of optimization problems in comparison with traditional methods since they need less initial parameters settings.

To evaluate how our approaches improve the robustness of evolutionary algorithms, we tested the approaches on a set of complex functions. The reported values for mean, best, and standard deviation of each function can give us a measure to see how our proposed methods improve the robustness of search algorithms against different problems.

1.3 Research Motivation

Our main motivation for this research work originates from scrutinizing different optimization algorithms and their capabilities of tackling various functions and search problems. As stated by No Free Lunch (NFL) theorem, there is no algorithm better than others over all cost functions [Wolpert and Macready, 1997]. It means, there is no guarantee for an algorithm to work well for all functions if it shows promising results for a particular category of them. Therefore, robustness has been one of the most desired features which motivates researchers to invent new methods which are less dependent on the kind of a problem than others. The aim of this research work is to improve robustness in evolutionary algorithms. In our thesis, we mostly emphasize on exploring different approaches to improving robustness in cultural algorithms regarding both belief and population spaces.

1.4 Thesis Contribution

In the thesis, we are going to improve the robustness of Cultural Algorithms in both components of population and belief spaces. In the population space, a new neigh-

borhood restructuring strategy is proposed which works based on a dynamic and irregular topology. In our approach, neighborhood restructuring occurs at a microscopic level, and every individual decides to change its neighborhood size. In the belief space, a new normative knowledge source is proposed which works based on the Confidence Interval concept inspired from Inferential Statistics. Also, we recognized that both Social fabric and PSO algorithm utilize the same social structure to facilitate social interactions between the individuals. So, we decided to use PSO in the population component of our proposed approach. We hypothesize that both of our approaches help the algorithm to resist against perturbations and not get affected by the fluctuations in the search space. The first approach lets the individuals adjust their relationships autonomously (self-organization). The second method makes the normative ranges in the belief space robust against fluctuations in the input data. Various benchmark functions have been used to evaluate the efficiency of evolutionary algorithms. As a reliable benchmark, we chose IEEE-CEC2015 function set which covers most of the desired properties for an optimization testbed such as multi-modality, copious local optima, and non-separability [Chen et al., 2014]. In our thesis, they are categorized in four categories: Unimodal, Simple multimodal, Hybrid, and Composite functions.

1.5 Thesis Outline

In the first chapter of this thesis, we give a general explanation of our motivation and contribution. The remaining chapters explain our research work in detail. Chapter 2 contains the related works done on the social fabric and the particle swarm optimization. This chapter is composed of 7 selected papers which 5 of them are about multi-population cultural algorithms and social fabric and how to apply them together. And, two of them are about PSO variants. In Chapter 3, we explain cultural

algorithms, social fabric, and PSO as our research background on evolutionary algorithms. Chapter 4 is composed of a detailed description of our proposed approaches to improve robustness in cultural algorithms. Chapter 5 explains IEEE-CEC2015 function set as the benchmark to evaluate the performance of our proposed methods against the standard social fabric algorithm. In Chapter 6, we present the result and comparison of the output of different methods on the benchmark functions in detail. Finally, in chapter 7, we conclude our work and suggest some new ideas for future works.

Chapter 2

Related Works

Many variants of CAs have been proposed in a vast range of different applications such as single and multi-objective optimization, dynamic problems, social interactions simulation. Here, we are interested in studying socially motivated and multi-population variants as some modern approaches in solving optimization problems.

2.1 Cultural Algoithms

2.1.1 Heterogeneous Multi-Population Cultural Algorithm

[Raeesi and Kobti, 2013] proposed a new architecture for cultural algorithms. In this approach, the whole population is divided into a set of independent sub-populations which work in parallel without direct communication. They referred to the works of [Xu et al., 2010], [Guo et al., 2011], [Vasile et al., 2011], and [Sharma et al., 2011]. As their motivation they stated that most of proposed variants of evolutionary algorithms suffers from immature convergence. This occurs because these algorithms can not hold the diversity at a reasonable level. Based on existing research works, they hypothesized that multi-population streategies would be a better choice as they have the potential to perfrom an efficient search on complex landscapes. In their approach,

the optimization parameters are divided among some heterogenous sub-populations. the sub-populations are called heterogenous because each sub-population is responsible for optimizing a different subset of parameters. Each sub-population represents a partial solution instead of a complete solution. To evaluate a partial solution, it gets completed by its complement parameter values from the belief space. The complete solution is evaluated based on a numerical optimization function. Also, to make the convergence process faster a simple local search strategy is incorporated into the proposed algorithm. The general architecture of their algorithm is presented in Figure 2.1

In the experiments, they considered the whole population size to be 1000 individ-

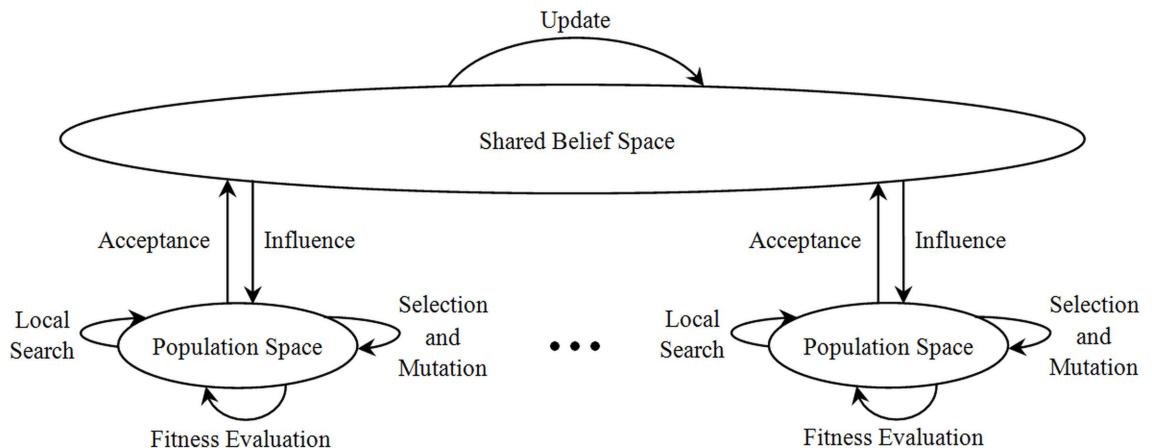


Figure 2.1: H-MPCA Architecture [Raeesi and Kobti, 2013]

uals. It is divided into 30 sub-populations. So, the size of each sub-population is 33. The algorithm runs for the maximum of 10000 generations and the local search strategy runs only for 10 iterations. They evaluated HMP-CA on a set of 8 complex optimization functions. It is able to find the minimum value for 7 functions out of 8. However, when the local search strategy is applied to the experiments, the proposed method outperforms all of the functions and it finds the optimum value very quickly. Ultimately, they claimed that their proposed approach is efficient in both time and space complexity.

2.1.2 The Social Fabric Approach as an Approach to Knowledge Integration in Cultural Algorithms

[Reynolds and Ali, 2008] begins with a brief introduction to socially motivated methods to problem solving. They referred to the works of [Hu et al., 2003], [Reynolds and Ali, 2007], and [Cheng et al., 2005]. It compares qualities of Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and Cultural Algorithms (CA) regarding the scale in which the interactions between agents occur. Figure 2.2 compares PSO, ACO, and CA in terms of the time and space continuum over which the social interactions occur. Individuals in ACO and PSO tend to interact in a relatively limited temporal and spatial scales. It is obvious because the agents in both ant and particle swarm algorithms exchange information with only other agents in their local neighborhood. On the other hand, cultural algorithms let the individuals interact together using various types of symbolic information emerged from complex cultural systems. In cultural algorithms the interactions among individuals occur indirectly through a shared belief space. So, cultural algorithms allow individuals interact in a global scale. Then, they asked the essential question of what social structures might

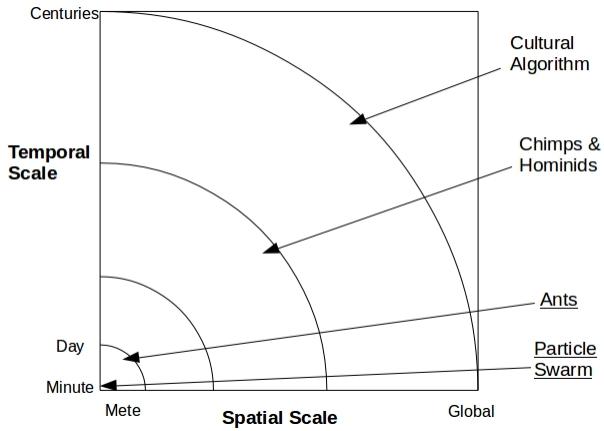


Figure 2.2: Scale of social interactions [Reynolds and Ali, 2008]

emerge alongside the search process?. To answer such questions, they introduced a new influence function which utilizes the social fabric phenomena. The old influ-

ence function assumes no interactions between agents and works based on the simple roulette wheel method. On the other hand, in the new influence function, the individuals are connected through a social network (fabric). Multiple layers of such networks could be employed in a population. The interplay of these network connection forms a social fabric. At each iteration, an individual could specify its controller knowledge source. In this approach, the controller knowledge source is chosen based on the majority of knowledge sources in the neighborhood of an individual. The neighborhood size of an individual is specified by the topology of the fabric. Inspired by Particle Swarm Optimization literature, different topologies could be taken into consideration to model the relationships among individuals. In their work, they only considered Ring and Square topologies. They stated that, the topology of the social fabric determines the extent to which the influence of knowledge sources could be spread thorough the network.

To evaluate the social fabric approach, they implemented it in Repast framework. Repast is a simulation tool for multi-agent systems. They created a cultural algorithms toolkit (CAT) to view the capabilities of cultural algorithms in solving various problems. They chose Cone World problem to evaluate and compare their approach with the standard cultural algorithm. The reason that they chose this problem is that by changing its parameters during the evolution process, it can show a dynamic behavior. So, Cone World problem provides an efficient way to test flexibility of search algorithms. They set the parameters of CAT as: 100 individuals, 100 cones and 1000 generations. They used ring and square topologies to from he social fabric. They stated that square topology works better than ring as it finds the solution after 250 iterations. While, the ring topology finds the best solution 450 iterations.

2.1.3 Robust Evolution Optimization at the Edge of Chaos: Commercialization of Culture Algorithms

[Che et al., 2010] aimed at commercializing Cultural Algorithm Toolkit (CAT) through developing a robust variant of it. By robustness, they mean to develop a cultural algorithm which is capable of being applied across a vast range of complex problems. At first, they referred to [Peng, 2005] as a standard model cultural algorithms which assumes no connection between individuals. Then, they referred to [Ali, 2008], which introduced the concept of social fabric to allow individuals interact together. The authors extended the work of Ali by allowing the social networks having a memory. In addition, they utilized a variety of different networks in order to determine the relationship between network and problem complexity.

They brought up the hypothesis that there might be multiple independent networks for different purposes such as kinship and economics. In such networks, there are always some individuals which are member of multiple networks and so, they can play the role of mediator between different networks. To preserve the diversity, the authors utilized a variety of different topologies such as Lbest, Square, Hexagon, Octagon, Hexadecagon, and Gbest.

They stated that in the previous work of [Ali, 2008], he employed an un-weighted majority win strategy to determine the controller knowledge source of an individual. It just relied on the count of each knowledge source in the neighborhood of each individual. The authors replaced it with a new strategy which uses the average fitness of each KSS instead of each KSS count. So, the performance of individuals in a neighborhood influences which knowledge source to be chosen for the next iteration.

To evaluate the robustness of the algorithm, the authors used Cone World Generator [Morrison and De Jong, 1999] as a dynamic problem. Referred to the work by [Lewin, 1999], they defined three classes of entropy in the cones world problem:

1. Fixed: There is a low entropy and the parameters of the environment do not tend to change at all.
2. Periodic: The environment parameters change in a regular period of time. So, the algorithm should be capable adapting itself regularly.
3. Chaotic: In this case, the parameters change without any order and no prediction could be made about them. In fact, it is more similar to real-world cases.

For the fixed category, the square topology successfully solved 84% of the problems and as the best topology. For the periodic case, the octagon topology showed a better performance than other topologies. And, for the chaotic category, Gbest showed a better result mostly in terms of average time to find a solution and the standard deviation. In summary, as the complexity of problems grows, there is the need for more connections between individuals in a social fabric to keep the robustness of the algorithm.

2.1.4 Socio-Cultural Evolution via Neighborhood-Restructuring in Intricate Multi-Layered Networks

[Ali et al., 2012] aimed at exploring the utilization of neighborhoods in the population level of cultural algorithms and see how it influences the knowledge swarming in the belief space. Their approach uses a dynamic neighborhood restructuring to preserve diversity efficiently. They referred to the research works of [Elsayed et al., 2011], [Asafuddoula et al., 2011], and [Asafuddoula et al., 2011]. Those papers proposed some adaptive methods which tried to make a trade-off between exploration and exploitation properties of evolutionary algorithms. Among the referred papers, the work by [Ali et al., 2010] used the social fabric phenomena to form multi-layered hierarchical network structures in both homogenous and heterogeneous networks.

Figure 2.3 describes the multi-layered structure.

The authors defined the social fabric phenomena as follows:

"The Social Fabric is a living informational skin created out of the engineered emergence of agents illustrating the tension between the individual and the community in a context of interaction between them"

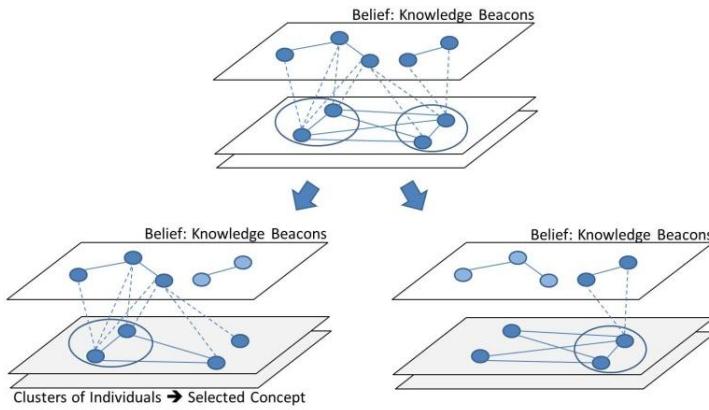


Figure 2.3: Multi-Layered Social Network with CA [Ali et al., 2012]

The informational skin is created by the connectivity of individuals together. The social fabric is used to combine the behaviors at both individuals and society levels. Then, they proposed a strategy to determine the controller knowledge source of each individual in each generation. In the strategy, the agents send the name of their controller knowledge source to their neighbor through the social fabric. Each individual picks the mostly used knowledge source in its neighborhood as its controller for the next iteration. In case of a tie between two or more knowledge sources, three tie-breaking strategies are introduced:

1. Most Frequently Used (MFU)
2. Random
3. Least Frequently Used (LFU)

They stated that their proposed approach is inspired from a previous work of [Reynolds et al., 2008]. The new idea was called Cultural Algorithm with Restructuring Layered Social Fabric (CARLSOF). In this approach, the whole population is divided into two layers of rudimentary and advanced members. There are some independent tribes in the population space which their best performing individuals form the advanced layer and the others form the rudimentary level. In the previous works, the topology of social fabrics were supposed to be fixed and homogenous. They utilized a variety of regular topologies to form the social fabric. The authors proposed a new strategy to enable the fabric to be restructured in the case of stagnation. Each tribe may decide to change its topology to a denser (with more connections) or sparser (with less connections). They referred to two different restructuring strategies as similar approaches. The first one was Layered Delaunay Triangulation which is based on voronoi diagram. The second approach was Random Rewiring Procedure which starts with a regular topology and then rewire each edge randomly with the probability p .

To evaluate the performance of CARLSOF, they used function set of IEEE-CEC2011 evolutionary competition. The algorithm was implemented in JAVA. The authors reported that CARLSOF was successful to enhance all of the functions in the testbed in terms of average, best, and worst obtained values. Also, they claimed that CARLSOF outperforms the best previously obtained results for European Space Agency (P12) and Casini (P13) problems results. They reported 2.983 km/sec compared to previous best 7.095. For p13, they reported 8.383091 km/sec compared to previous best 8.3832.

2.1.5 Leveraged Neighborhood Restructuring in Cultural Algorithms for Solving Real-World Numerical Optimization Problems

[Ali et al., 2016] made an overall review of related works on Cultural Algorithms and Social Fabric [Peng, 2005], [Reynolds and Ali, 2008], [Chen et al., 2006], and [Kennedy, 1999]. They introduced the concept of social fabric as an infrastructure which facilitates the propagation of the influence of the knowledge sources through the population space. The whole population is divided into multiple small sized tribes. Unlike other PSO-based multi-swarm variants, the tribal sub-swarms change their topology during the evolution process to keep diversity against stagnations.

The tribes are organized in a two-layer structure of advanced and rudimentary classes. The advanced class is composed of best performing individuals of each tribe. From each tribe, two exemplars are chosen. The first one is the best of explorer knowledge sources (Normative and Topographic) and the second one is the best of exploiter knowledge sources (Situational). Figure 2.4 describes the two-layer structure. The authors utilized only three kinds of knowledge sources: Normative, Topographic, and Situational. They claimed that, other types of knowledge sources are suitable for dynamic problems. However, they used a set of static problems to evaluate their approach. The authors divided the evolution process of CAs into three stages: the seclusion stage , the rapport stage , and the cohesive stage. In the seclusion stage, the tribes evolve independently and without any exchange of information. Then, in the rapport stage, the tribes start to exchange knowledge via the advanced class. Also, the neighborhood restructuring strategy is launched in each tribe. So, the tribes have the capability to restructure their topology to keep diversity and avoid local optima. The first two stages ensure that diversity has been kept in the initial iterations of the search process. Finally, in the third stage, all the tribes are merged together

and continue the search process as a single CA model. Based on the categorization

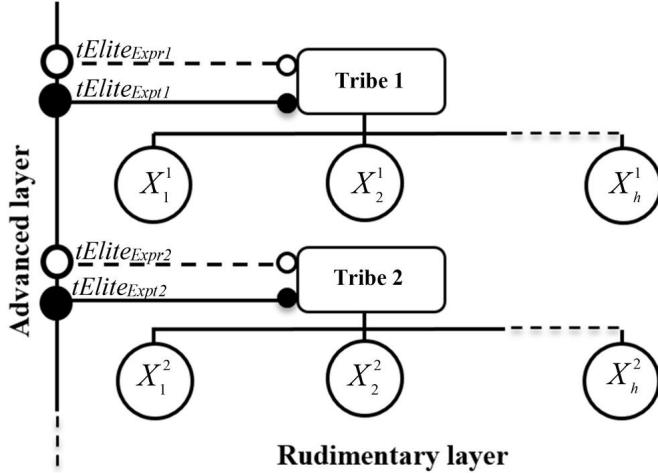


Figure 2.4: Two-class taxonomy of the tribal CA [Ali et al., 2016]

proposed in [De Oca et al., 2009], the authors claimed that their approach is heterogeneous regarding update-rule heterogeneity and neighborhood heterogeneity. Since the topology of each tribe is changing during the evolution process, the tribes might use different topologies at the same time. So, it could be considered as heterogeneous neighborhood restructuring. Also, their approach utilizes update-rule heterogeneity because, there are individuals with different roles (explorer and exploiter).

In the experimental results section, the authors used IEEE-CEC2011 competition on testing evolutionary algorithms on real-world numerical optimization problems. They presented an extended comparison of their approach with other proposed methods. At first, the authors tested the approach (T-SCANeR) with different values for these parameters: tie-breaking rule, M_{thresh} , and number of elites. There is no best value for tie-breaking rule as it is problem-dependent. For the M_{thresh} parameter, the results show that the best value is 50. The best value for n_{tElite} is 2. The second experiment was on varying the window size within which the social fabric is applied and aggregated (W_{size}). The best reported value for W_{size} is 20.

In the two first experiments the best values for the parameters were determined. Based on the obtained values, the authors compared T-SCANeR with five other evolution-

ary algorithms on the IEEE-CEC2011 which is a set of 18 functions. T-SCANeR managed to outperform for most of the functions except for T_3 , T_4 , T_6 , and $T_{11.5}$. Problems T_{12} (full messenger problem) and T_{13} (cassini problem) are associated with the European Space Agency (ESA). The authors claimed that T-SCANeR outperformed other methods by 2.193724 km/s for the messenger problem and 8.383090 for the cassini problem.

2.2 Particle Swar Optimization

2.2.1 Tribe-PSO: A novel global optimization algorithm and its application in molecular docking

[Chen et al., 2006] proposed a new variant of Particle Swarm Optimization (PSO) called Tribe-PSO for the primary purpose of molecular docking in chemometrics. As some previous research work, they referred to [Jones et al., 1997] and [Clerc and Kennedy, 2002]. Their approach is inspired from Hierarchical Fair Competition concept [Jianjun et al., 2002]. They divided the whole population into some tribes and the evolution process into three phases. The tribes are organized into two layers of basic and upper individuals.

The individuals in each tribe are completely isolated from other tribes. So, they form the basic layer. On the other hand, the best members of each tribe can see the other tribes and exchange information with their best members as well. The problem-solving process is divided into three phases: isolated, communing, and united. In the first phase, the tribes are completely isolated and there is no exchange of information. In the second phase, the two-layered model is formed and the tribes begin to exchange information through their best performing individuals. In the third phase, all the tribes are merged into a single popualtion. Then, it operates as basic PSO model until meeting some stopping criteria. The autohrs claimed that their approach helps

the individuals preserving diversity and avoiding local optima against multi-modal solution spaces.

The authors used two testbeds to evaluate and compare the performance of Tribe-PSO with standard PSO. The first was De Jong's function set and the second was a test set of 100 receptor-ligand X-ray structures selected for docking benchmark. In the De Jong's testbed, the basic PSO showed a better performance in the isolated phase. However, in the communing phase Tribe-PSO converged to a better value than basic PSO. In the unity phase, the basic PSO seemed to get stuck in a local optimum. However, Tribe-PSO continued to accelerate convergence and got better results than basic PSO. In the docking benchmark, Tribe-PSO was compared to the AutoDock library. Four parameters are calculated after 10 independent runs: Best, Run1, Average, and Standard Deviation of the results. The relative difference of the four benchmark factors between Tribe-PSO and AutoDock were calculated. The results for the four factors showed that Tribe-PSO leads to a better performance than AutoDock.

2.2.2 Heterogeneous Particle Swarm Optimizers

[De Oca et al., 2009] peresented a survey on heterogeneous variants of Paritcle Swarm Optimization (PSO). They claim that the homogenous models have been attractive because of their simplicity in conceptual and application levels. However, heterogeneous models are ubiquitous in nature. Here, heterogeneity means the individuals may differ from each other regarding their parameters and search behavior.

At first, the authors presented a breif description of three well-known variants of PSO: Accelerated PSO [Zhang et al., 2003], Fully-informed PSO [Mendes et al., 2004], and Bare Bones PSO [Kennedy, 2003]. Then, they authors categirzed the heterogeneous variants of PSO into four categories:

1. Neighborhood

2. Model of Influence

3. Update Rule

4. Parameters

Neighborhood heterogeneity refers to the cases that the topology of the swarm is not regular. This type of heterogeneity occurs when the neighborhood size of each individual is different. They claimed that the neighborhood heterogeneity allows some population to be more influential than others. Individuals with higher number of connections have the potential to attract more individuals through the search process [Kennedy et al., 2001].

Model of Influence heterogeneity refers to the situations that the individuals employ different strategies to specify their informers. The word Informer refers to an individual which is going to influence another individual.

Update-rule heterogeneity means the individuals utilize different strategies to update their position in the search space. This kind of heterogeneity makes it possible for the individuals to explore the search space in several ways. Also, the particles can play different but complementary roles. For example, some of them may tend to explore unseen parts of the solution space and some others only follow those scout individuals. The second type are the exploiters.

Parameter heterogeneity occurs when some individuals in a group which follow the same update rule use different update rule's parameter settings. Having different search parameters, even in a group of similar particles, leads to various search behaviors which improves the level of diversity. The authors referred to [Mendes, 2004] and [Montes de Oca and Stützle, 2008] which utilize different initial values for the parameters such as acceleration coefficient, maximum velocities and inertia weight.

To compare the mentioned categories, the authors cared two test cases. The first one compared two PSO variants with different update rules: Velocity-based and Bare

bones swarm. The evaluation results confirmed that velocity-based outperformed the other one. The second test case compared two PSO variants with different models of influence: best-of-neighborhood and fully-informed swarm. The evaluation results showed that the fully-informed algorithm outperfromed the best-of-neighborhood.

2.3 Chapter Conclusion

From the chosen research works, we will be utilizing the concept of heterogeneous neighborhood structures by [De Oca et al., 2009] to improve the robustness of social fabric-based cultural algorithm [Ali et al., 2016]. We replace the population component of [Ali et al., 2016] with PSO algorithm.

Chapter 3

Evolutionary Algorithms

This chapter presents a detailed description of related evolutionary algorithms such as cultural algorithms, particle swarm optimization, and their social variations. In this section, we try to give a brief description of those evolutionary algorithms as a background to our proposed approaches.

3.1 Evolutionary Algorithms

Evolutionary computing is a research area within computer science. As the name suggests, it is a particular flavor of computing, which draws inspiration from the process of natural evolution. In fact, they are computer programs which try to solve and optimize complex problems by simulating the behavior of natural systems. They utilize evolutionary operators such as crossover and mutation to improve the quality of a population of solutions [Burke et al., 2005].

Evolutionary algorithms start with a population of randomly generated solutions for a particular problem. Then, the algorithm modifies the solutions in an iteration-based process of some finite number of generations. The modification occurs through applying the so-called evolutionary operators such as crossover and mutation. The evolutionary operators might be binary or unary. For example, the crossover is a bi-

nary operator because it combines two solutions (individuals) to generate a new one. On the other hand, mutation is a unary operator because it makes random modifications on a single solution to improving its performance [Eiben and Smith, 2003]. The performance of each is evaluated using a fitness function. The fitness function represents the problem that needs to be solved or optimized. Usually, the fitness function is chosen from NP problems which are hard to solve by traditional problem-solving methods. In each iteration of an evolutionary algorithm, the evolutionary operators are applied to the individuals and the best performing offsprings will be transferred to the next generation. This process continues until meeting some stopping criteria which are already defined by a human user. Some examples of evolutionary algorithms are:

1. Genetic Algorithms
2. Evolutionary Programming
3. Differential Evolution

However, the evolutionary algorithms are not restricted to biological processes. Some researchers have drawn inspiration from social systems to find solutions to complex problems. The complex and coordinated behavior of swarms not only fascinates biologists but also is an inspiration to computer scientists [Bonabeau et al., 1999]. Ant colonies and birds flocking are remarkable examples of coordinated collective behavior that emerges without centralized control. Swarm intelligence is a field of computer science that invents computational methods for solving problems in a way that is inspired by the behavior of real swarms and colonies. Principles of self-organization and communication (local and indirect) are essential to understanding the complex collective behavior [Stützle, 2009]. There are different types of swarm-based algorithms such as:

1. Particle Swarm Optimization (PSO)

2. Ant Colony Optimization (ACO)
3. Cultural Algorithms (CA)

3.2 Cultural Algorithms

Cultural Algorithms (CA) were introduced by Reynolds as a type of population-based problem-solving approaches. CA combines biological evolution with socio-cognitive concepts to yield an optimization approach based on a dual inheritance theory [Reynolds, 1994]. As defined by [Durham, 1991], culture is a “system of symbolically encoded conceptual phenomena that are socially and historically transmitted within and between populations”. From the definition, it can be stated that in cultural systems, evolution occurs at two levels: Macro-evolutionary level and micro-evolutionary level. Cultural algorithms define the evolution process through the cooperation of three distinct components:

1. Belief Space (Macro-evolutionary Level)
2. Population Space (Micro-evolutionary Level)
3. Communication Protocol

3.2.1 Belief Space

Belief space keeps different kinds of knowledge obtained from the individuals’ experience during the evolution process. It extracts the knowledge from the population and stores the knowledge in various formats called knowledge sources (KS). Each knowledge source extracts and keeps knowledge about a particular aspect of the search space.

After each iteration, the best performing individuals are chosen and sent to the belief space to be utilized by the knowledge sources. The stored knowledge is used to bias

the search process in the population space. Five types of knowledge sources have been identified in the belief space:

1. Situational Knowledge: Successful exemplars of individuals
2. Normative Knowledge: The best range of value for each parameter
3. Topographic Knowledge: The best areas of the search space
4. Domain knowledge: The domain ranges for all the parameters and the best exemplars
5. Temporal Knowledge: Knowledge about the past changes in a dynamic environment

3.2.2 Population Space

In the population space, any population-based algorithm could be used. In the earlier variants of cultural algorithms, only GA was used. However, researchers utilized other population-based algorithms such as PSO and EP in the population component. In each generation, the best individuals are sent to the belief space to update the knowledge sources. Then, the belief space influences the population through the search process. Figure 3.1 describes the components of cultural algorithms.

3.2.3 Communication Protocol

In cultural algorithms, the belief space and the population communicate together through a two-way protocol. The population space sends the best individuals to the belief space using the acceptance function to update the knowledge sources. Then, the belief space bias the search direction of the population space through the influence function.

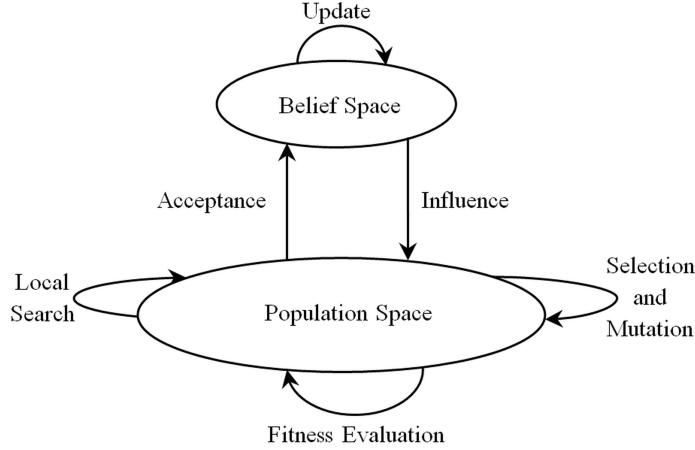


Figure 3.1: Cultural Algorithms [Raeesi and Kobti, 2013]

3.3 Social Fabric-based Cultural Algorithms

Social Fabric is a dynamic grid of information flow in which the individuals' interactions happen. The fabrics (networks) are created by the connectivity of each agent with other agents in a dynamic structure. The topology of the network controls the rate and type of interactions [Reynolds and Ali, 2008]. Like a multi-population model, there are multiple independent subpopulations (tribes) which are networked together [Ali et al., 2012].

In the Social Fabric idea, the influence of the belief space is propagated through the population using a multi-layered network of connections. There are Z tribes comprised of H individuals which form two layers: rudimentary and advanced [Ali et al., 2012] [Ali et al., 2016]. The members of each tribe are connected in a regular topology independent from other tribes. At this level, they form the rudimentary layer. From each tribe, the best performing individuals (elites) are connected. These connections create the advanced layer which is responsible for mediating the flow of information between different tribes.

3.3.1 Evolution Phases

The whole evolution process is split into three phases: seclusion, rapport, and cohesive. In the first stage, each tribe evolves as an independent basic CA model with no communication between tribes. In the second step, the advanced layer is formed by connecting elites of each tribe. Then, tribes start to exchange information during their evolution process. Ultimately, in the third step, all the tribes are merged into one CA model. Then the search process continues until meeting some stopping criteria.

3.3.2 Strategic Neighborhood Restructuring

In Social Fabric literature, Strategic Restructuring is a technique to help individuals to get rid of stagnation where there are copious local optima in the search landscape. Each tribe maintains a particular topology until it gets stagnated in a local optimum for a certain number of iterations. Then, the topology is reinitialized to motivate the individuals for a new search. Here, four types of topologies are utilized: Ring, Mesh, Hybrid-Tree, and Global [Ali et al., 2016]. Figure 3.2 describes how the process of neighborhood restructuring occurs.

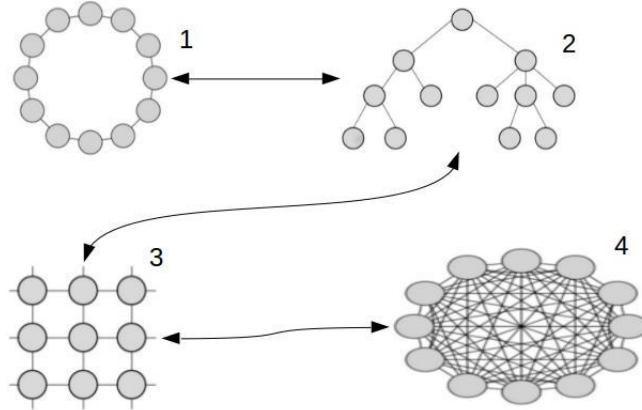


Figure 3.2: Standard Neighborhood Restructuring Process

3.3.3 Social fabric based influence function

In this model, the individuals might decide to change their controller KS using the majority of KSs which they receive from their neighborhood. Here, Majority Voting is used to find the controller KS of an individual [Che et al., 2010]. Figures 3.3 describes the social fabric influence function. In the case of a tie, some tie-breaking rules are deployed such as MFU (most frequently used), LFU (least frequently used), Direct (the direct influencing KS), Random (a random choice), Last-used (the KS which controlled the KS in the last iteration) [Ali et al., 2012]. In the equation 3.1 the sum denotes the counts of KSs in i th node neighborhood and ψ_i is its controller KS. τ_i is the net affecting KS for the next iteration [Ali et al., 2016] [Sterling, 2004].

$$\tau_i = \sum_{j \in Nbr(i)} m_{ij} + \psi_i \quad (3.1)$$

The Social Fabric approach can be generalized on different topologies as follows:

$$KS(t+1) = \begin{cases} KS_i, & \forall KS_j \in \{KS - KS_i\} \Rightarrow weight(KS_i) > weight(KS_j) \\ KS_{cr}, & otherwise \end{cases} \quad (3.2)$$

Where KS is the set of all knowledge sources, $KS_i, KS_j \in KS$. $weight(KS_i)$ is the number of neighbors that belong to the knowledge source KS_i . KS_{cr} denotes the knowledge source chosen by a tie-breaking rule.

3.4 Particle Swarm Optimization

The initial idea for particle swarm optimization of Kennedy and Eberhart were essentially aimed at producing computational intelligence by utilizing simple models of social interaction, rather than purely single-agent cognitive capabilities.

In PSO, some simple-structured individuals (the particles) moving around in the

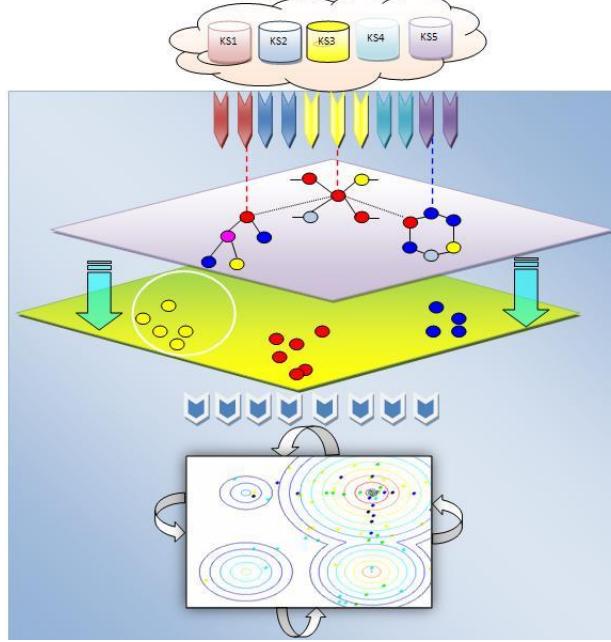


Figure 3.3: Social Fabric Influence Function[Ali and Reynolds, 2009]

search space of a function, and each particle evaluates the objective function based on its current location. Then, each particle determines its movement direction and velocity through the search space by combining its historical best experience and the best (best-fitness) particle in its visible neighborhood in the swarm, with some random fluctuations for keeping diversity. This process repeats at each iteration. Eventually, the swarm as a whole, like a flock of birds collectively searching for food sources, is similar to move around for finding an extremum of the fitness function. Each particle is comprised of a position vector and velocity vector [Bratton and Kennedy, 2007]. Particles adjust their velocities and positions as follows:

$$v_{id}^{(t+1)} = w \cdot v_{id}^{(t)} + c_1 r_1 (p_{id} - x_{id}^{(t)}) + c_2 r_2 (p_{gd} - x_{id}^{(t)}) \quad (3.3)$$

$$x_{id}^{(t+1)} = x_{id}^{(t)} + v_{id}^{(t+1)} \quad (3.4)$$

Where v_{id} and x_{id} are the velocity and position of i th particle. $c1$ and $c2$ are two positive constants. $r1$ and $r2$ are randomly generated numbers in $[0,1]$ range. w is the

inertia weight of which restricts the velocity of a particle. p_{id} is the best experience of the particle and p_{gd} is the best solution in its neighborhood. Figure 3.4 describes how the particle interact together in PSO.

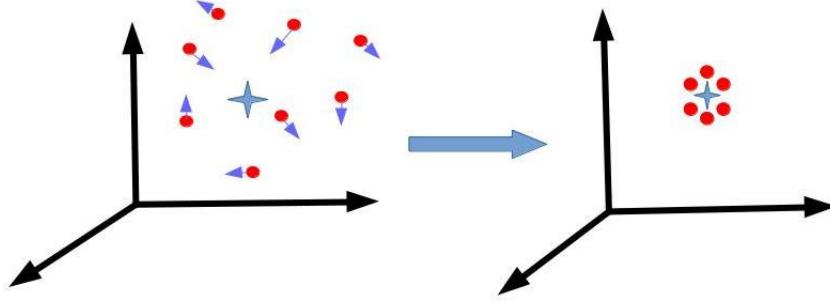


Figure 3.4: Social interaction model of PSO

3.4.1 Tribe-PSO

Similar to Social Fabric model, the whole population is divided into some tribes. The tribes form a two-layer structure of networks, and the whole process consists of three phases [Chen et al., 2006]. The individuals in each tribe are completely isolated from other tribes. So, they form the basic layer. On the other hand, the best members of each tribe can see the other tribes and exchange information with their best members as well. The problem-solving process is divided into three phases: isolated, communing, and united. In the first phase, the tribes are completely isolated and there is no exchange of information. In the second phase, the two-layered model is formed and the tribes begin to exchange information through their best performing individuals. In the third phase, all the tribes are merged into a single population. Then, it operates as basic PSO model until meeting some stopping criteria. In fact, the idea of Social Fabric originates from Tribe-PSO. But the network structure is utilized to propagate the influence of knowledge sources in the belief space [Ali et al., 2016]. In the thesis, we use the social fabric for both PSO interactions and knowledge propagation of the belief space. Figure 3.5 describes the architecture of Tribe-PSO.

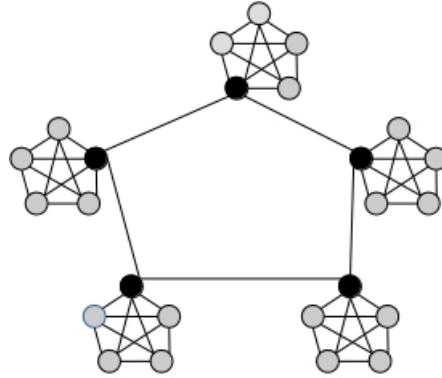


Figure 3.5: Tribal-PSO

3.5 Chapter Conclusion

This chapter presents a detailed description of evolutionary and social methods such as cultural algorithms, social fabrics, and PSO. The chapter was focused on Tribal variants of before mentioned approaches and how to deploy social relationships among the tribes' members.

Chapter 4

Proposed Approaches: Improving Robustness in Social Fabric

Inspired by natural systems, many evolutionary algorithms have been proposed to solve various optimization problems. These algorithms are expected to exhibit a consistent problem-solving behavior against different optimization landscapes. Unfortunately, as stated by No Free Lunch (NFL) theorem by [Wolpert and Macready, 1997], there is no algorithm better than others over all cost functions. It means, there is no guarantee for an algorithm to work well for all functions if it shows promising results for a particular category of them. Therefore, robustness has been one of the most desired features which motivates researchers to invent new methods which are less dependent on the kind of a problem than others. Here, robustness means we need to develop search strategies which are capable of adapting themselves across different landscapes which might vary regarding aspects such as multimodality and the number of local optima.

In this section, we are going to improve the robustness of CAs in both population space and belief space components. In the population space, a new neighborhood restructuring strategy will be proposed which aims at microscopic inspections for

stagnation regarding individuals' local experience. Then, in the belief space, a new model of Normative KS will be proposed, which defines the normative ranges based on Confidence Interval inspired from Inferential Statistics. It stops the normative KS to be affected by sudden fluctuations in the input data.

4.1 Self-organization

A self-organized system is a group of agents with specific behavioral patterns which could not be predicted from the simple behaviors of the individuals who make up the system. [Kennedy et al., 2001] described self-organization as follows:

"Self-organization The ability of some systems to generate their form without external pressures, either wholly or in part. It can be viewed as a system's constant attempts to organize itself into ever more complex structures, even in the face of the constant forces of dissolution described by the second law of thermodynamics."

Some of the primary attributes of self-organizing systems are listed below:

1. Self-organizing systems usually exhibit the behaviors that appear to be spontaneous order.
2. Self-organization can be considered as a system's constant attempts to organize itself into a variety of complex structures, even in the face of the forces of deviation (Robustness).
3. The overall status of a self-organizing system is an emergent property of all the ingredients of the system.
4. Interconnected components of the system become organized in a meaningful way based on local interactions of the components.

5. Complex systems have the potential to self-organize themselves.

6. The self-organization process works close to the "edge of chaos".

In the section, we will propose a new approach to improve the robustness of cultural algorithms regarding self-organization.

4.2 Irregular Neighborhood Restructuring

As proposed by [Ali et al., 2016], when the agents of a tribe get stuck in a local optimum, then they choose a topology with fewer connections such as ring topology to motivate exploration. When the agents lack information, the topology is changed to a denser topology like Mesh, and ultimately Global. Whenever a tribe does not make progress for M_{thresh} iterations, then the algorithm decides on upgrading/downgrading the current topology to other topologies. Downgrading happens by moving in the direction of gbest → tree → mesh → lbest and Upgrading occurs in the direction of lbest → mesh → tree → gbest. In our proposed approach, the restructuring process occurs at a microscopic level. There is no daemon process for inspecting stagnation. Every agent checks its performance for stagnation. If it gets stuck in a local optimum, it decides to upgrade/downgrade its neighborhood. The proposed strategy is described in the algorithm 1. If the particle is the best in its neighborhood, it starts to decrease the number of connections to motivate exploration. However, if it is not the best, it needs to increase the neighborhood size to facilitate exploitation. Here, the topology is dynamic and irregular and the neighborhood size is different for each agent. So, it could be considered as a heterogeneous variant of CAs [De Oca et al., 2009]. The ultimate topology of the fabric is formed through local interactions of the agents. In this way, it improves the robustness of CAs regarding self-organization concept [Kennedy et al., 2001]. Psudo-code 1 describes the irregular neighborhood restructuring algorithm in detail.

```

if  $fitness(x_i) > bestSoFar_i$  then
    if  $stagnationCounter \geq TiggerThreshold$  then
        if  $x_i = x_{best}$  then
            | index = selected randomly from  $x_i$ 's neighborhood
            | remove  $x_{index}$  from  $x_i$ 's neighborhood
        else
            | index = selected from  $\{S - x_i\}'s neighborhood\}$ 
            | add  $x_{index}$  to  $x_i$ 's neighborhood
        end
         $stagnationCounter = 0$ 
    else
        |  $stagnationCounter = stagnationCounter + 1$ 
    end
else
    |  $stagnationCounter = 0$ 
end

```

Algorithm 1: Irregular Neighborhood Restructuring

4.3 Confidence based Normative Knowledge Source

The current version of Normative KS is quite vulnerable to temporary fluctuations in the pattern of input data. The size of Normative ranges is subject to change dramatically with any temporal fluctuations. In this section, we are going to replace the ranges in the standard Normative KS with Confidence Interval from Inferential Statistics. Confidence-based changes are more robust against instantaneous changes in the input pattern. The update process of standard normative ranges is as follows:

$$lb_j(t+1) = \begin{cases} x_{i,j}(t), & x_{i,j}(t) \leq lb_j(t) \text{ or } f(X_i) < PL_j(t) \\ lb_j, & \text{otherwise} \end{cases} \quad (4.1)$$

$$ub_j(t+1) = \begin{cases} x_{i,j}(t), & x_{i,j}(t) \geq ub_j(t) \text{ or } f(X_i) < PU_j(t) \\ ub_j, & \text{otherwise} \end{cases} \quad (4.2)$$

The following is the definition of normative ranges based on Confidence Interval concept [Proakis, 1985].

$$lb_j = \bar{x}_j - q \cdot \frac{\sigma_j}{\sqrt{n}} \quad (4.3)$$

$$ub_j = \bar{x}_j + q \cdot \frac{\sigma_j}{\sqrt{n}} \quad (4.4)$$

where \bar{x}_j is the mean of j th dimension, σ_j is the standard deviation of j th dimension and q is the confidence coefficient.

Chapter 5

Experimental Setup

In this chapter, we explain the experimental setup, how to set the parameters and the optimization functions as the benchmark to evaluate the efficiency of our proposed approaches.

5.1 Description

In this section, we describe IEEE-CEC2015 as the function set which we have chosen for our benchmark optimization purpose [Chen et al., 2014]. IEEE-CEC2015 is a set of 15 functions with different properties such as multi-modality, copious local optima, and non-separability. All test functions are minimization problems defined as follows:

$$Y = f(x_1, x_2, x_3, \dots, x_D) \quad (5.1)$$

where D is the number of dimensions.

Before evaluation, all the vectors are shifted and rotated as described in [Chen et al., 2014]. $\mathbf{o}_i = [o_i1, o_i2, \dots, o_iD]$ is the shifted global optimum, which is randomly distributed in [-80,80] D For convenience, the same search ranges are defined for all test functions as $[-100, 100]^D$

5.2 Benchmark Functions

In this section, we describe the IEEE-CEC2015 functions and their properties as a well-known benchmark adopted by many researchers to evaluate innovative ideas in solving complex optimization problems.

5.2.1 Unimodal Functions

Rotated Bent Cigar Function

$$f_1(x) = x_1^2 + 10^6 \sum_{i=2}^D x_i^2 \quad (5.2)$$

$$F_1(x) = f_1(M(x - o_1)) + F_1^* \quad (5.3)$$

Properties:

1. Unimodal
2. Non-separable
3. Smooth but narrow ridge

Rotated Discus Function

$$f_2(x) = 10^6 x_1^2 + \sum_{i=2}^D x_i^2 \quad (5.4)$$

$$F_2(x) = f_2(M(x - o_2)) + F_2^* \quad (5.5)$$

Properties:

1. Unimodal
2. Non-separable
3. With one sensitive direction

5.2.2 Simple Multimodal Functions

Shifted and Rotated Weierstrass Function

$$f_3(x) = \sum_{i=1}^D \left(\sum_{k=0}^{kmax} [a^k \cos(2\pi b^k (x_i + 0.5))] \right) - D \sum_{k=0}^{kmax} [a^k \cos(2\pi b^k \cdot 0.5)] \quad (5.6)$$

where $a=0.5$, $b=3$, and $kmax=20$.

$$F_3(x) = f_3(M(\frac{0.5(x - o_3)}{100})) + F_3^* \quad (5.7)$$

Properties:

1. Multi-modal
2. Non-separable
3. Continuous but differentiable only on a set of points

Shifted and Rotated Schwefel's Function

$$f_4(x) = 418.9829 \times D - \sum_{i=1}^D g(z_i), z_i = x_i + 4.209687462275036e+002 \quad (5.8)$$

$$F_4(x) = f_4(M(\frac{1000(x - o_4)}{100})) + F_4^* \quad (5.9)$$

Properties:

1. Multi-modal
2. Non-separable
3. Local optima's number is huge and second better local optimum is far from the global optimum.

Shifted and Rotated Katsuura Function

$$f_5(x) = \frac{10}{D_2} \prod_{i=1}^D \left(1 + i \sum_{j=1}^{32} \frac{|2^j x_i - rand(2^j x_i)|}{2^j} \right)^{\frac{10}{D^{1.2}}} - \frac{10}{D^2} \quad (5.10)$$

$$F_5(x) = f_5(M(\frac{5(x - o_5)}{100})) + F_5^* \quad (5.11)$$

Properties:

1. Multi-modal
2. Non-separable
3. Continuous everywhere yet differentiable nowhere

Shifted and Rotated HappyCat Function

$$f_6 = |\sum_{i=1}^D x_i^2 - D|^{0.25} + \frac{0.5 \sum_{i=1}^D x_i^2 + \sum_{i=1}^D x_i}{D + 0.5} \quad (5.12)$$

$$F_6(x) = f_6(M(\frac{5(x - o_6)}{100})) + F_6^* \quad (5.13)$$

Properties:

1. Multi-modal
2. Non-separable

Shifted and Rotated HGBat Function

$$f_7 = |(\sum_{i=1}^D x_i^2)^2 - (\sum_{i=1}^D x_i)^2|^{0.25} + \frac{0.5 \sum_{i=1}^D x_i^2 + \sum_{i=1}^D x_i}{D + 0.5} \quad (5.14)$$

$$F_7(x) = f_7(M(\frac{5(x - o_7)}{100})) + F_7^* \quad (5.15)$$

Properties:

1. Multi-modal
2. Non-separable

Shifted and Rotated Expanded Griewank's plus Rosenbrock's Function

$$f_8(x) = f_{11}(f_{10}(x_{x_1, x_2})) + f_{11}(f_{10}(x_{x_2, x_3})) + \cdots + f_{11}(f_{10}(x_{x_{D-1}, x_D})) + f_{11}(f_{10}(x_{x_D, x_1})) \quad (5.16)$$

$$F_8(x) = f_8(M(\frac{5(x - o_8)}{100}) + 1) + F_8^* \quad (5.17)$$

Properties:

1. Multi-modal
2. Non-separable

Shifted and Rotated Expanded Scaffer's F6 Function

$$g(x, y) = 0.5 + \frac{(\sin^2(\sqrt{x^2 + y^2}) - 0.5)}{(1 + 0.001(x^2 + y^2))^2} \quad (5.18)$$

$$f_9(x) = g(x_1, x_2) + g(x_2, x_3) + \cdots + g(x_{D-1}, x_D) + g(x_D, x_1) \quad (5.19)$$

$$F_9(x) = f_9(M(x - o_9) + 1) + F_9^* \quad (5.20)$$

Properties:

1. Multi-modal
2. Non-separable

5.2.3 Hybrid Functions

Hybrid Function 1

This function is a hybrid of three functions: Modified Schwefel's function, Rastrigin's function, and High Conditioned Elliptic function.

$$F_{10}(x) = 0.3 \times F_4(x) + 0.3 \times F_{12}(x) + 0.4 \times F_{13}(x) \quad (5.21)$$

Hybrid Function 2

This function is a hybrid of 4 functions: Griewank's function, Weierstrass function, Rosenbrock's function, and Scaffer's F6 function.

$$F_{11}(x) = 0.2 \times F_{11}(x) + 0.2 \times F_3(x) + 0.3 \times F_{10}(x) + 0.3 \times F_9(x) \quad (5.22)$$

Hybrid Function 3

This function is a hybrid of 5 functions: Katsuura function, HappyCat function, Expanded Griewank's plus Rosenbrock's function, Modified Schwefel's function, and Ackley's function.

$$F_{12}(x) = 0.1 \times F_5(x) + 0.2 \times F_6(x) + 0.2 \times F_8(x) + 0.2 \times F_4(x) + 0.3 \times F_{14}(x) \quad (5.23)$$

5.2.4 Composite Functions

The general format of composite function is as follows:

$$F(x) = \sum_{i=1}^N \{\omega_i \times [\lambda_i g_i(x) + bias_i]\} + f^* \quad (5.24)$$

$F(x)$: composition function

$g_i(x)$: i^{th} basic function used to construct the composition function

N : number of basic functions

ω_i : new shifted optimum position for each $g_i(x)$, define the global and local optima's position.

$bias_i$: defines which optimum is global optimum.

σ_i : used to control each $g_i(x)$'s coverage range, a small σ_i give a narrow range for that $g_i(x)$

λ_i : used to control each $g_i(x)$'s height

w_i : weight value for each $g_i(x)$, calculated as follows:

$$w_i = \frac{1}{\sqrt{\sum_{j=1}^D (x_j - o_{ij})^2}} \exp\left(-\frac{\sum_{j=1}^D (x_j - o_{ij})^2}{2D\sigma_i^2}\right) \quad (5.25)$$

Now, the value of ω_i weight is calculated as:

$$\omega_i = \frac{w_i}{\sum_{i=1}^n w_i} \quad (5.26)$$

Composition Function 1

Five types of basic functions are combined to construct this function:

$N = 5$, $\sigma = [10, 20, 30, 40, 50]$, $\lambda = [1, 1e-6, 1e-26, 1e-6, 1e-6]$, bias = [0, 100, 200, 300, 400]

g_1 : Rotated Rosenbrock's Function f_{10}

g_2 : High Conditioned Elliptic Function f_{13}

g_3 : Rotated Bent Cigar Function f_1

g_4 : Rotated Discus Function f_2

g_5 : High Conditioned Elliptic Function f_{13}

Properties:

1. Multi-modal
2. Non-separable
3. Asymmetrical
4. Different properties around different local optima

Composition Function 2

Three types of basic functions are combined to construct this function:

$N = 3$, $\sigma = [10, 30, 50]$, $\lambda = [0.25, 1, 1e-7]$, bias = [0, 100, 200]

g_1 : Rotated Schwefel's function f_4

g_2 : Rotated Rastrigin's function f_{12}

g_3 : Rotated High Conditioned Elliptic function f_{13}

Properties:

1. Multi-modal
2. Non-separable
3. Asymmetrical
4. Different properties around different local optima

Composition Function 3

Five types of basic functions are combined to construct this function:

$N = 5$, $\sigma = [10, 10, 10, 20, 20]$, $\lambda = [10, 10, 2.5, 25, 1e-6]$, bias = [0, 100, 200, 300, 400]

g_1 : Rotated HGBat Function f_7

g_2 : Rotated Rastrigin's Function f_{12}

g_3 : Rotated Schwefel's Function f_4

g_4 : Rotated Weierstrass Function f_3

g_5 : Rotated High Conditioned Elliptic Function f_{13}

Properties:

1. Multi-modal
2. Non-separable
3. Asymmetrical
4. Different properties around different local optima

5.3 Parameters Settings

We used the same initial values for the parameters as presented by [Ali et al., 2016]:

- Population Size: 90
- Number of tribes: 10
- The window-size for applying the social influence with restructuring (Wsize): 20
- The proportion of the best agents to be sent to the belief space (Pa): 0.25
- The number of elites in each tribe (nelite): 2
- The threshold trigger for restructuring (Mthresh): 50
- Tie-breaking rule (TieR): MFU
- The maximum number of function evaluations (MaxFES): 150000
- The social factor (Sf) is an integer value variable that takes a value between 0 and 3. Note that these figures correspond to topologies, lbest, von-Neumann,n-star-bus, and gbest.

Here, we use MaxFES as a stopping criterion. There are 20 independent runs for each function. And each function is tested for 10 and 30 number of dimensions.

Chapter 6

Evaluation, Analysis and Comparisons

In this chapter, we present a detailed comparison of our two approaches: Irregular neighborhood restructuring (ISFCA) and Confidence-based normative knowledge source (CSFCA) with other methods. We chose the standard social fabric algorithm by [Ali et al., 2016] and Tribe-PSO by [Chen et al., 2006] for the purpose of comparison, as both of them utilize social structures and a tribal approach.

We compare the approaches on each function with 10 and 30 dimensions. For each function, an overall comparison is presented regarding mean, median, best, and standard deviation (StdDev). Then, average fitness values of 10 experiments with different random generator settings are presented.

6.1 Function 1: Bent Cigar Function

In table 6.1 and figure 6.1, we can see that both of our approaches (ISFCA and CSFCA) and TPSO outperform the standard SFCA impressively with 98% and 55% for optimization of 10 dimensions. In the case of 30-dimension optimization, ISFCA and CSFCA perform with 60% and 42% improvement respectively.

Table 6.1: function-1, dimension-10

	SFPSO	CSFEP	SFEP	TPSO
Median	5.721885E+06	5.113078E+08	8.122664E+09	5.426664E+05
Mean	1.576602E+08	4.091655E+09	9.246107E+09	2.479394E+08
Best	5.711750E+06	9.279149E+05	9.908642E+08	5.415067E+05
StdDev	3.066335E+08	6.639431E+09	8.500530E+09	3.993037E+08

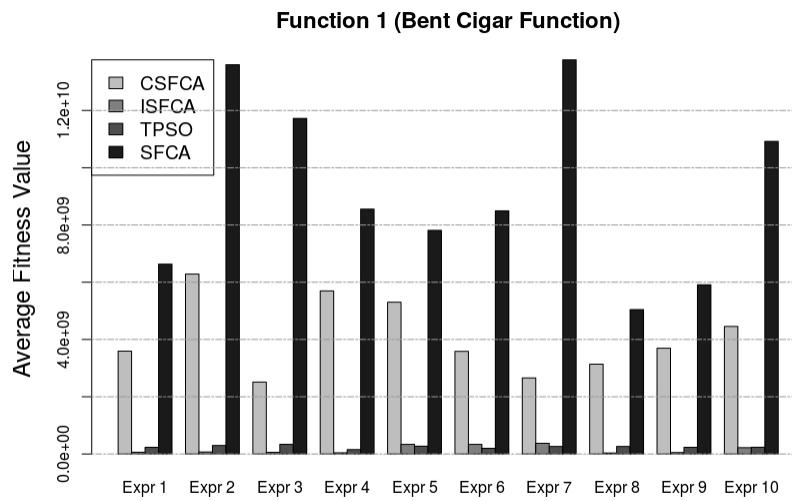


Figure 6.1: Average fitness values for Function 1 with 10 dimensions

Table 6.2: function-1, dimension-30

	SFPSO	CSFEP	SFEP	TPSO
Median	1.224376E+10	9.035849E+09	3.381544E+10	1.223994E+10
Mean	1.497176E+10	2.168689E+10	3.786293E+10	1.718683E+10
Best	1.075684E+10	3.249525E+08	8.929425E+09	1.136511E+10
StdDev	6.549615E+09	2.551255E+10	2.853221E+10	7.102879E+09

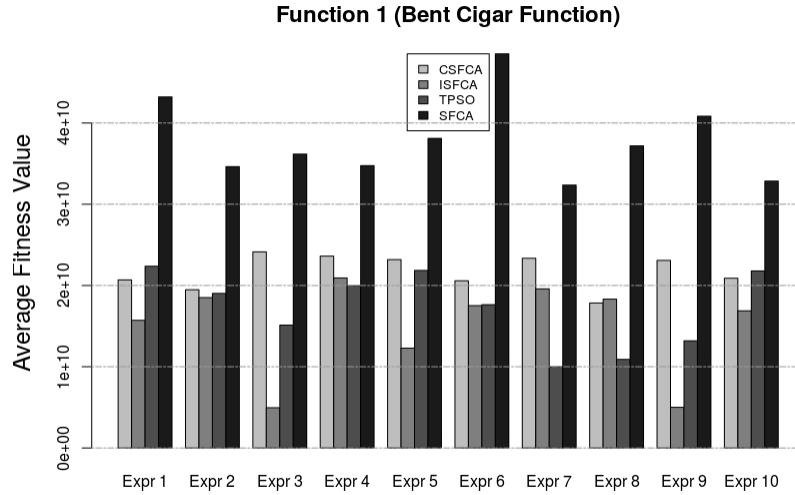


Figure 6.2: Average fitness values for Function 1 with 30 dimensions

6.2 Function 2: Discus Function

As we can see in the table 6.3 and 6.3, for 10-dimension optimization, ISFCA and CSFCA improve by 99% and 42% on the function 2. As explained in table 6.4 and 6.4, they outperform the standard algorithm by 99% and 95% for 30-diemension optimization.

Table 6.3: function-2, dimension-10

	SFPSO	CSFEP	SFEP	TPSO
Median	1.763602E+04	1.858882E+04	1.966669E+09	1.989622E+04
Mean	1.970646E+04	2.045944E+09	3.574556E+09	2.202554E+04
Best	1.690419E+04	1.426333E+04	2.467511E+04	1.722714E+04
StdDev	5.285568E+03	4.083561E+09	4.508859E+09	5.505069E+03

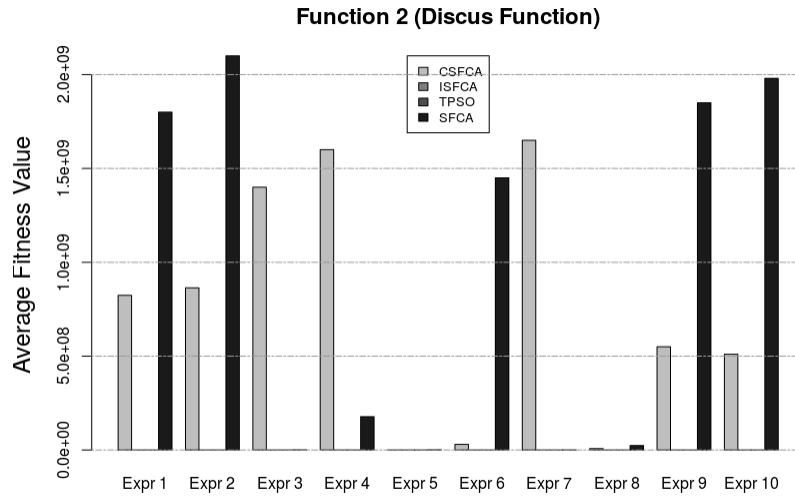


Figure 6.3: Average fitness values for Function 2 with 10 dimensions

Table 6.4: function-2, dimension-30

	SFPSO	CSFEP	SFEP	TPSO
Median	7.057468E+04	6.106335E+04	8.669496E+07	1.338066E+05
Mean	7.324758E+04	1.090201E+08	2.266584E+09	1.324195E+05
Best	6.816396E+04	5.556673E+04	7.322705E+04	1.112664E+05
StdDev	1.112414E+04	2.214664E+08	4.323029E+09	1.359207E+04

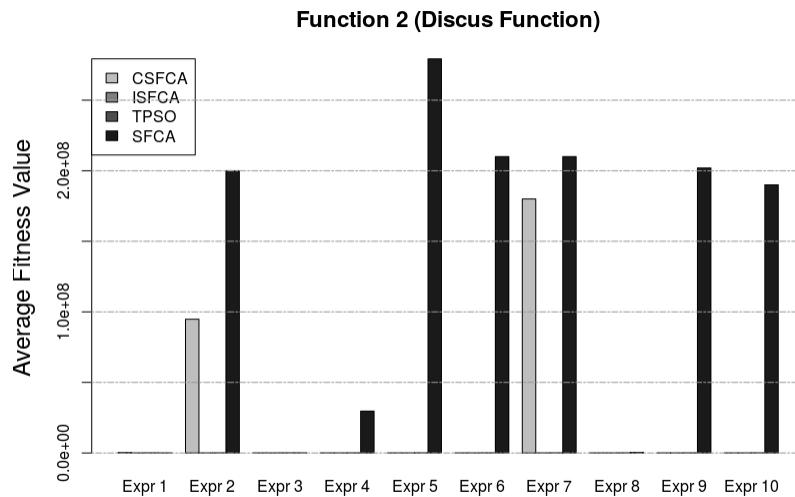


Figure 6.4: Average fitness values for Function 2 with 30 dimensions

6.3 Function 3: Weierstrass Function

As you can see in Tables 6.5 and 6.6 and Figures 6.5 and 6.6, the improvement of our approaches is trivial. However, it is still better than SFCA.

Table 6.5: function-3, dimension-10

	SFPSO	CSFEP	SFEP	TPSO
Median	3.053639E+02	3.088023E+02	3.106131E+02	3.059917E+02
Mean	3.055362E+02	3.095236E+02	3.108567E+02	3.064904E+02
Best	3.047026E+02	3.075572E+02	3.086619E+02	3.055813E+02
StdDev	9.238688E-01	2.153735E+00	2.160320E+00	9.113892E-01

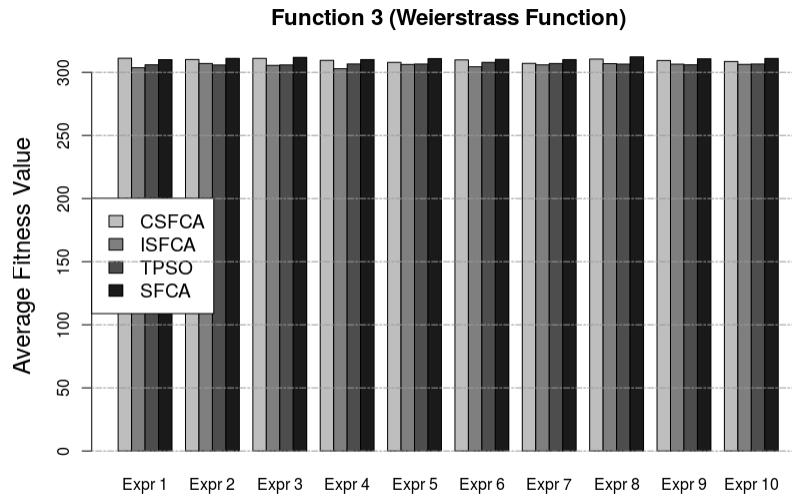


Figure 6.5: Average fitness values for Function 3 with 10 dimensions

Table 6.6: function-3, dimension-30

	SFPSO	CSFEP	SFEP	TPSO
Median	3.288747E+02	3.395129E+02	3.414242E+02	3.276385E+02
Mean	3.307785E+02	3.400480E+02	3.410312E+02	3.305742E+02
Best	3.274619E+02	3.352212E+02	3.360418E+02	3.275333E+02
StdDev	3.242337E+00	4.748334E+00	4.694844E+00	3.905358E+00

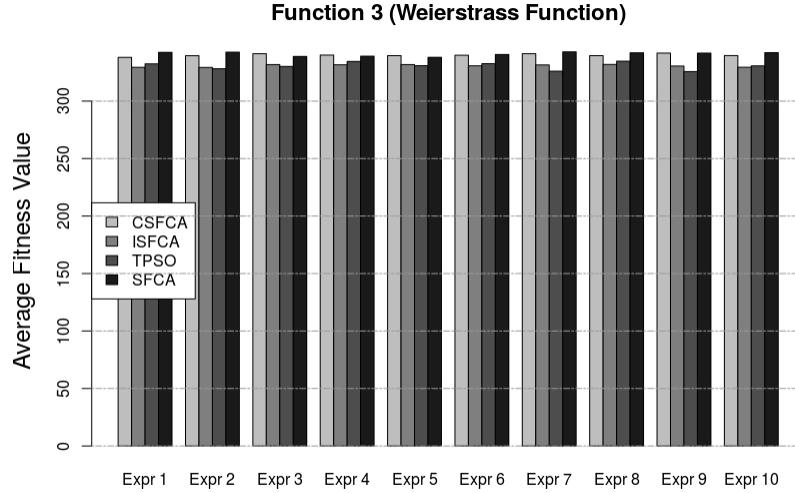


Figure 6.6: Average fitness values for Function 3 with 30 dimensions

6.4 Function 4: Modified Schwefel's Function

Table 6.7 and figure 6.7 show that in the case 10-dimension optimizatoin, ISFCA performs better by 18% and CSFCA by 19%. However, for the 30-dimension case, only CSFCA outperform SFCA by 21% as shown in Table 6.8 and Figure 6.8.

Table 6.7: function-4, dimension-10

	SFPSO	CSFEP	SFEP	TPSO
Median	1.374025E+03	1.198259E+03	1.740208E+03	1.326440E+03
Mean	1.401458E+03	1.392015E+03	1.725446E+03	1.391022E+03
Best	1.249122E+03	6.135802E+02	8.405862E+02	1.201363E+03
StdDev	1.709634E+02	8.047924E+02	8.388958E+02	2.174364E+02

Table 6.8: function-4, dimension-30

	SFPSO	CSFEP	SFEP	TPSO
Median	6.870764E+03	5.098037E+03	6.819341E+03	7.117825E+03
Mean	6.964474E+03	4.998230E+03	6.375121E+03	7.270199E+03
Best	6.625647E+03	1.377132E+03	3.463489E+03	6.882440E+03
StdDev	4.205720E+02	3.054933E+03	2.436783E+03	4.387157E+02

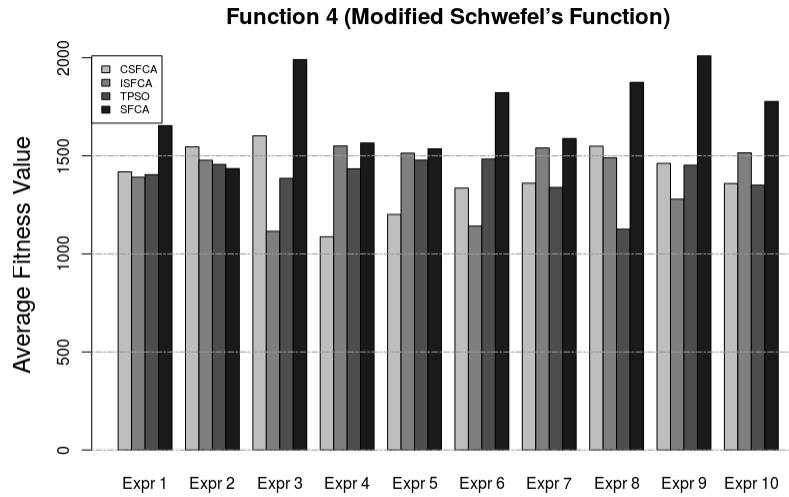


Figure 6.7: Average fitness values for Function 4 with 10 dimensions

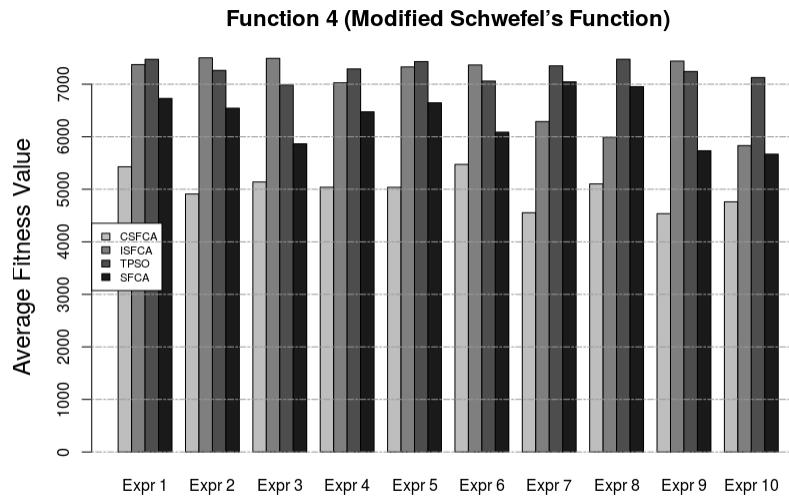


Figure 6.8: Average fitness values for Function 4 with 30 dimensions

6.5 Function 5: Katsuura Function

As you can see in Tables 6.9 and 6.10 and Figures 6.9 and 6.10, the results of all the approaches are almost the same.

Table 6.9: function-5, dimension-10

	SFPSO	CSFEP	SFEP	TPSO
Median	5.012550E+02	5.014254E+02	5.019767E+02	5.012505E+02
Mean	5.013300E+02	5.017117E+02	5.023857E+02	5.013223E+02
Best	5.010726E+02	5.007002E+02	5.011836E+02	5.011289E+02
StdDev	2.684750E-01	1.132619E+00	1.339239E+00	2.057213E-01

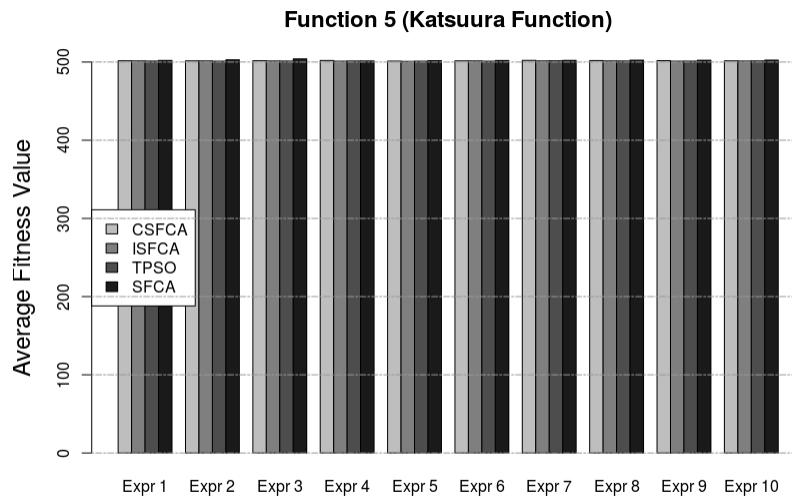


Figure 6.9: Average fitness values for Function 5 with 10 dimensions

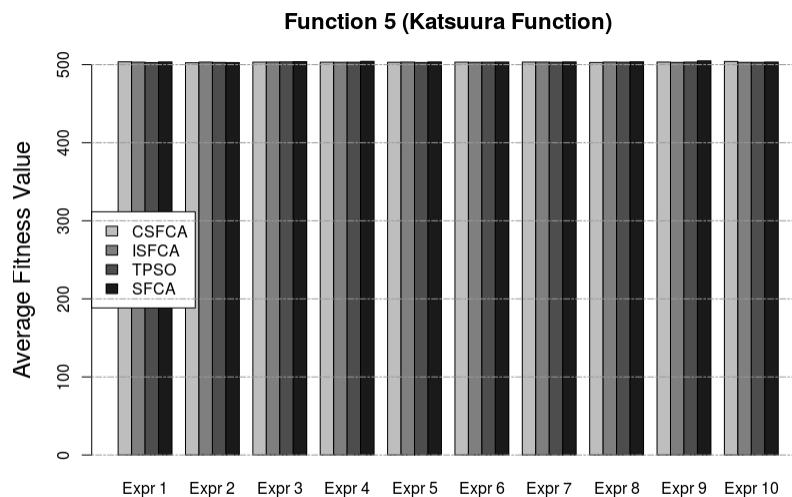


Figure 6.10: Average fitness values for Function 5 with 30 dimensions

Table 6.10: function-5, dimension-30

	SFPSO	CSFEP	SFEP	TPSO
Median	5.029073E+02	5.025217E+02	5.030453E+02	5.028359E+02
Mean	5.030805E+02	5.031380E+02	5.036162E+02	5.029678E+02
Best	5.028153E+02	5.016618E+02	5.020560E+02	5.026209E+02
StdDev	3.548877E-01	1.669277E+00	1.678840E+00	3.015601E-01

6.6 Function 6: HappyCat Function

As you can see in Tables 6.11 and 6.12 and Figures 6.11 and 6.11, the improvement of our approaches is trivial.

Table 6.11: function-6, dimension-10

	SFPSO	CSFEP	SFEP	TPSO
Median	6.004688E+02	6.015392E+02	6.033087E+02	6.005062E+02
Mean	6.005623E+02	6.025225E+02	6.036813E+02	6.009515E+02
Best	6.004334E+02	6.005685E+02	6.018524E+02	6.005062E+02
StdDev	3.200289E-01	2.304279E+00	1.898523E+00	6.229300E-01

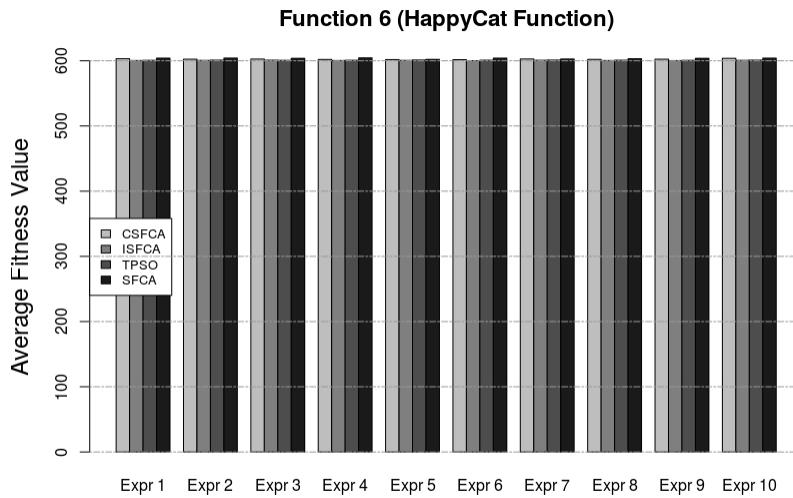


Figure 6.11: Average fitness values for Function 6 with 10 dimensions

Table 6.12: function-6, dimension-30

	SFPSO	CSFEP	SFEP	TPSO
Median	6.025572E+02	6.038615E+02	6.054925E+02	6.010077E+02
Mean	6.030236E+02	6.039768E+02	6.056628E+02	6.019309E+02
Best	6.024192E+02	6.010681E+02	6.041570E+02	6.010077E+02
StdDev	7.579661E-01	2.740738E+00	1.433152E+00	1.224478E+00

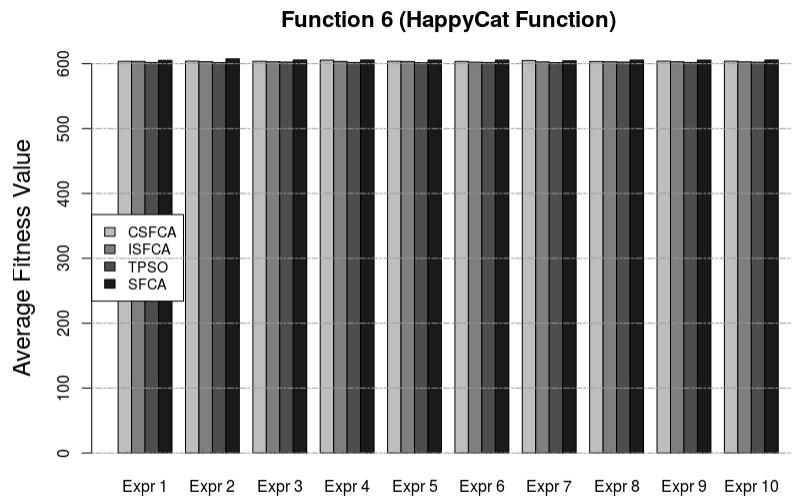


Figure 6.12: Average fitness values for Function 6 with 30 dimensions

6.7 Function 7: HGBat Function

As you can see in Tables 6.13 and 6.14 and Figures 6.13 and 6.13, the improvement of our approaches is not so much. In the case of 10-dimension optimization, it is about 5% and for the 30-dimension case, it is about 9%.

Table 6.13: function-7, dimension-10

	SFPSO	CSFEP	SFEP	TPSO
Median	7.008041E+02	7.081532E+02	7.341129E+02	7.004902E+02
Mean	7.019942E+02	7.260979E+02	7.418000E+02	7.038384E+02
Best	7.006188E+02	7.007965E+02	7.100632E+02	7.004902E+02
StdDev	2.635216E+00	3.539268E+01	3.490056E+01	5.486938E+00

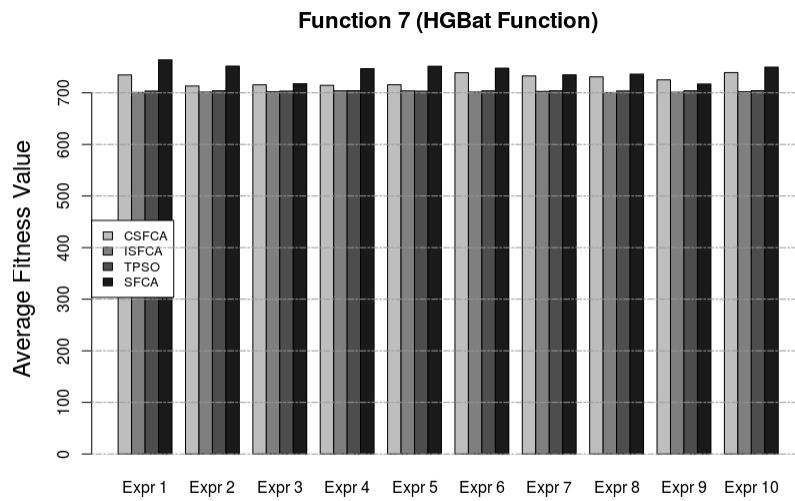


Figure 6.13: Average fitness values for Function 7 with 10 dimensions

Table 6.14: function-7, dimension-30

	SFPSO	CSFEP	SFEP	TPSO
Median	7.291294E+02	7.477774E+02	8.042494E+02	7.280204E+02
Mean	7.389013E+02	7.605963E+02	8.116680E+02	7.498652E+02
Best	7.271223E+02	7.024000E+02	7.544377E+02	7.262179E+02
StdDev	1.569694E+01	5.981939E+01	5.740507E+01	2.791729E+01

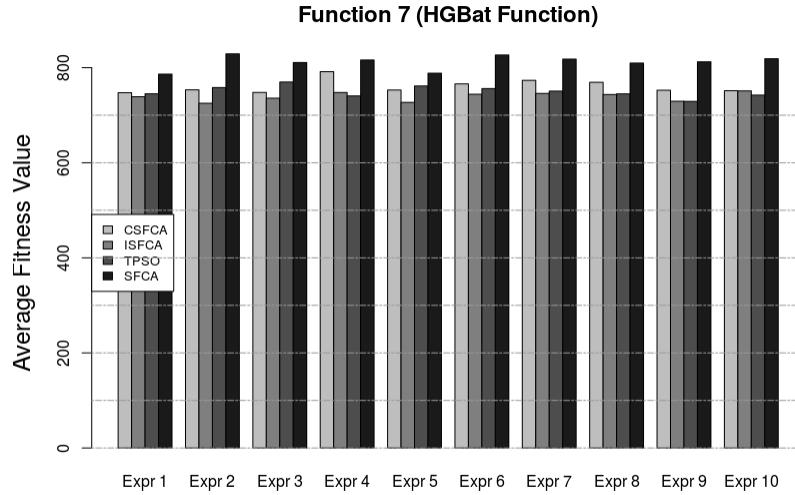


Figure 6.14: Average fitness values for Function 7 with 30 dimensions

6.8 Function 8: Griewank's plus Rosenbrock's Function

In table 6.15 and figure 6.15, we can see that both of our approaches (ISFCA and CSFCA) and TPSO outperform the standard SFCA impressively with 99% and 77% for optimization of 10 dimensions. In the case of 30-dimension optimization, ISFCA and CSFCA perform with 97% and 52% improvement respectively as shown in Table 6.16 and Figure 6.16.

Table 6.15: function-8, dimension-10

	SFPSO	CSFEP	SFEP	TPSO
Median	8.060488E+02	4.762535E+03	5.638811E+05	8.057399E+02
Mean	8.327824E+02	3.080861E+05	1.374142E+06	8.319941E+02
Best	8.060488E+02	8.475602E+02	4.118304E+03	8.057399E+02
StdDev	1.428379E+02	5.970746E+05	1.940514E+06	7.254239E+01

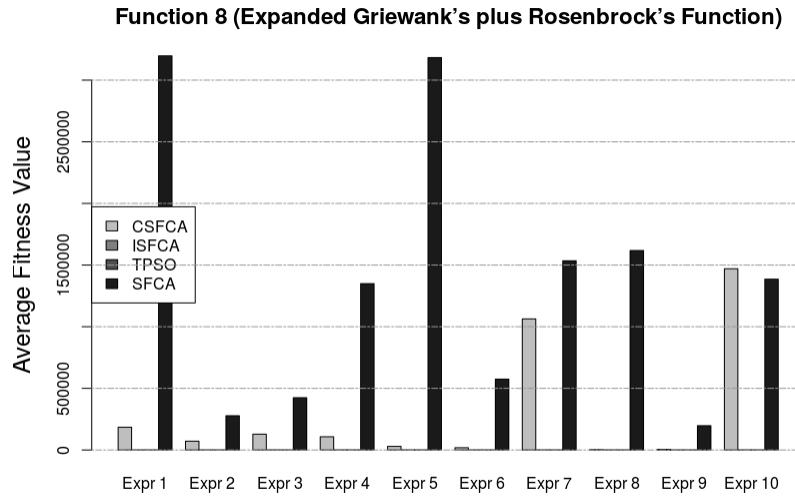


Figure 6.15: Average fitness values for Function 8 with 10 dimensions

Table 6.16: function-8, dimension-30

	SFPSO	CSFEP	SFEP	TPSO
Median	1.139271E+05	3.872060E+05	3.562129E+06	8.406430E+05
Mean	3.363145E+05	7.477703E+06	1.541796E+07	1.645666E+06
Best	5.240269E+04	1.095824E+03	8.508643E+04	4.126489E+05
StdDev	6.891847E+05	1.270040E+07	2.340250E+07	1.667678E+06

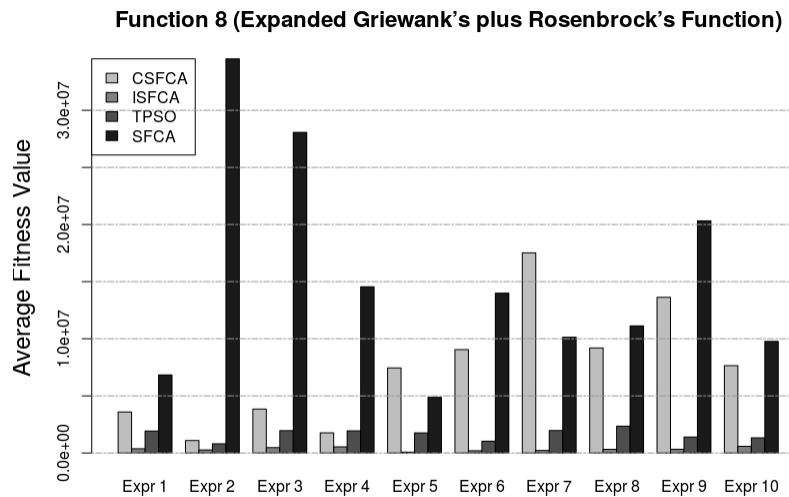


Figure 6.16: Average fitness values for Function 8 with 30 dimensions

6.9 Function 9: Expanded Scaffer's F6 Function

In Tables 6.17 and 6.18 and Figures 6.17 and 6.18, we can see that there is not a considerable improvement and all the methods perform almost the same.

Table 6.17: function-9, dimension-10

	SFPSO	CSFEP	SFEP	TPSO
Median	9.036094E+02	9.035775E+02	9.037811E+02	9.035661E+02
Mean	9.036469E+02	9.036343E+02	9.038043E+02	9.036178E+02
Best	9.035325E+02	9.032589E+02	9.033602E+02	9.035094E+02
StdDev	1.008688E-01	3.372815E-01	4.187602E-01	1.037992E-01

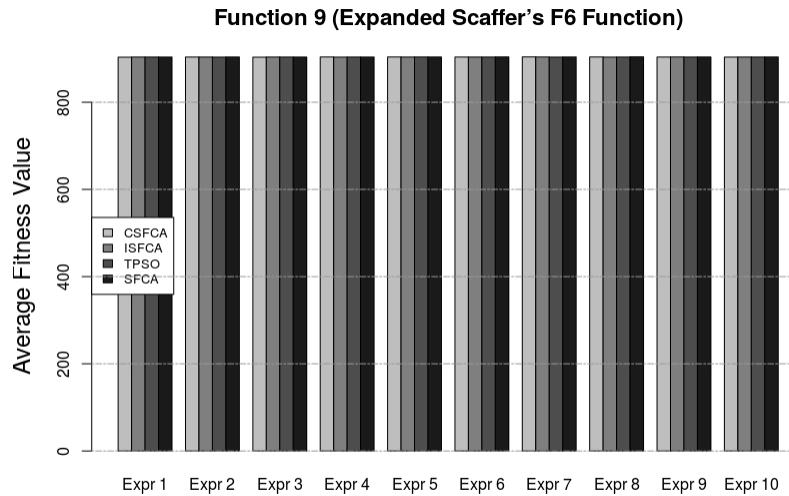


Figure 6.17: Average fitness values for Function 9 with 10 dimensions

Table 6.18: function-9, dimension-30

	SFPSO	CSFEP	SFEP	TPSO
Median	9.134898E+02	9.134569E+02	9.136834E+02	9.135212E+02
Mean	9.135258E+02	9.133575E+02	9.136351E+02	9.135977E+02
Best	9.133757E+02	9.126562E+02	9.131192E+02	9.134243E+02
StdDev	1.312660E-01	5.882330E-01	4.913793E-01	1.390313E-01

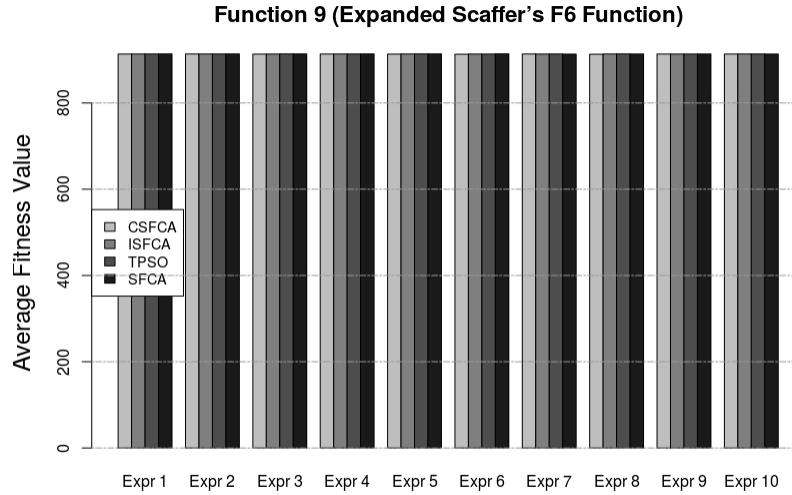


Figure 6.18: Average fitness values for Function 9 with 30 dimensions

6.10 Function 10: Hybrid Function 1

In the 10-dimension case, Table 6.19 and Figure 6.19 show an impressive improvement for both ISFCA and CSFCA approaches by 99% and 77% respectively. For the 30-dimension case, ISFCA and CSFCA outperform SFCA by 97% and 51% respectively as shown in Table 6.20 and Figure 6.20.

Table 6.19: function-10, dimension-10

	SFPSO	CSFEP	SFEP	TPSO
Median	5.078678E+04	5.565684E+05	1.462417E+06	3.479607E+04
Mean	6.855882E+04	1.390710E+06	1.250589E+07	6.576307E+04
Best	2.148022E+04	2.365329E+03	6.578523E+03	1.417589E+04
StdDev	7.234730E+04	1.778552E+06	2.276703E+07	7.783437E+04

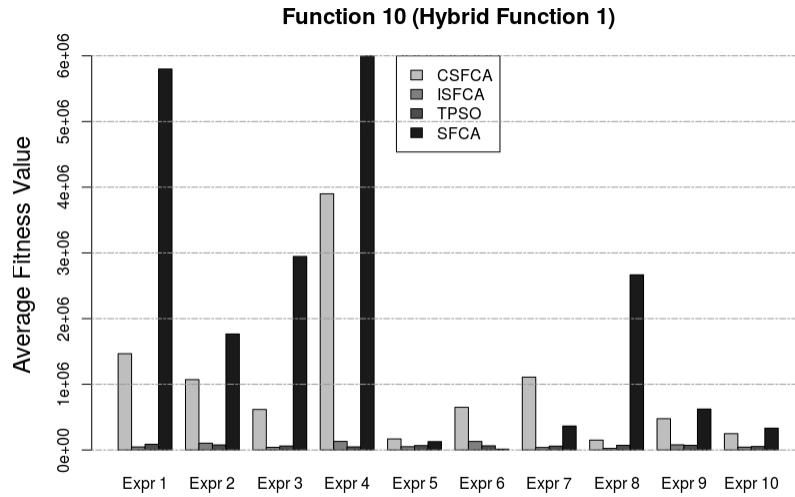


Figure 6.19: Average fitness values for Function 10 with 10 dimensions

Table 6.20: function-10, dimension-30

	SFPSO	CSFEP	SFEP	TPSO
Median	1.257686E+07	2.886032E+07	7.068932E+07	1.524856E+07
Mean	1.288355E+07	5.268560E+07	7.171894E+07	1.914266E+07
Best	6.072906E+06	2.225892E+06	8.682100E+06	1.311979E+07
StdDev	7.703664E+06	5.803312E+07	5.952516E+07	8.464172E+06

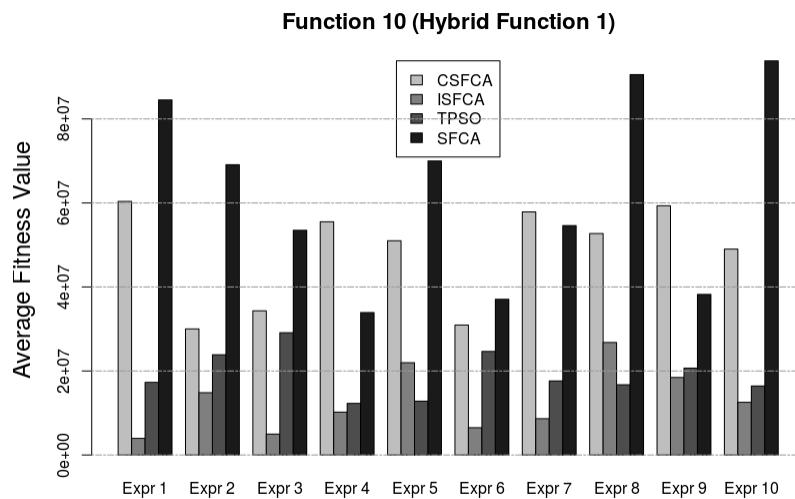


Figure 6.20: Average fitness values for Function 10 with 30 dimensions

6.11 Function 11: Hybrid Function 2

Table 6.21 and Figure 6.21 show a trivial improvement for the 10-dimension case. On the other hand, Table 6.22 and Figure 6.22 explain that ISFCA and CSFCA outperform the standard algorithm by 30% and 15% respectively.

Table 6.21: function-11, dimension-10

	SFPSO	CSFEP	SFEP	TPSO
Median	1.104725E+03	1.109982E+03	1.111399E+03	1.104917E+03
Mean	1.105085E+03	1.137076E+03	1.140188E+03	1.105442E+03
Best	1.104062E+03	1.106581E+03	1.105492E+03	1.104723E+03
StdDev	1.339530E+00	5.229237E+01	4.994351E+01	9.340507E-01

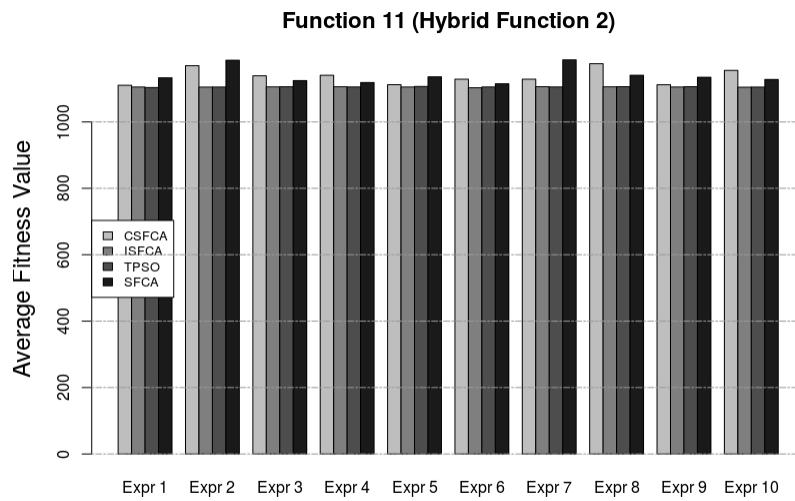


Figure 6.21: Average fitness values for Function 11 with 10 dimensions

Table 6.22: function-11, dimension-30

	SFPSO	CSFEP	SFEP	TPSO
Median	1.188478E+03	1.246676E+03	1.561269E+03	1.134562E+03
Mean	1.197912E+03	1.456495E+03	1.724513E+03	1.174516E+03
Best	1.153360E+03	1.155965E+03	1.290852E+03	1.134562E+03
StdDev	4.334944E+01	4.589486E+02	5.277303E+02	6.235017E+01

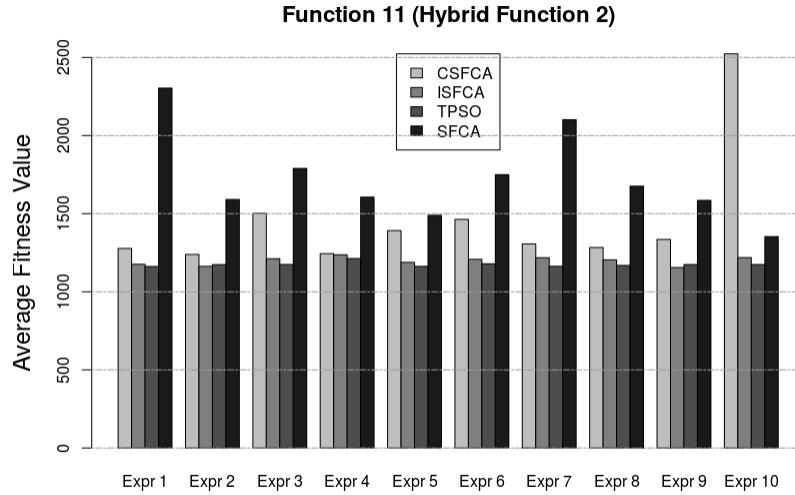


Figure 6.22: Average fitness values for Function 11 with 30 dimensions

6.12 Function 12: Hybrid Function 3

Both of ISFCA and CSFCA approaches perform much better than the standard algorithm in both 10-dimension and 30-dimension scenarios. Table 6.23 and Figure 6.23 show that ISFCA and CSFCA improve the performance by 93% and 82% for the 10-dimension case. Table 6.24 and Figure 6.24 indicate that ISFCA and CSFCA improve the performance by 99% and 68% for the 30-dimension case.

Table 6.23: function-12, dimension-10

	SFPSO	CSFEP	SFEP	TPSO
Median	1.278429E+03	1.470304E+03	2.561160E+03	1.274117E+03
Mean	1.284340E+03	3.740383E+03	2.109208E+04	1.290392E+03
Best	1.247398E+03	1.342194E+03	1.419410E+03	1.259420E+03
StdDev	4.080435E+01	4.569942E+03	3.705284E+04	4.016558E+01

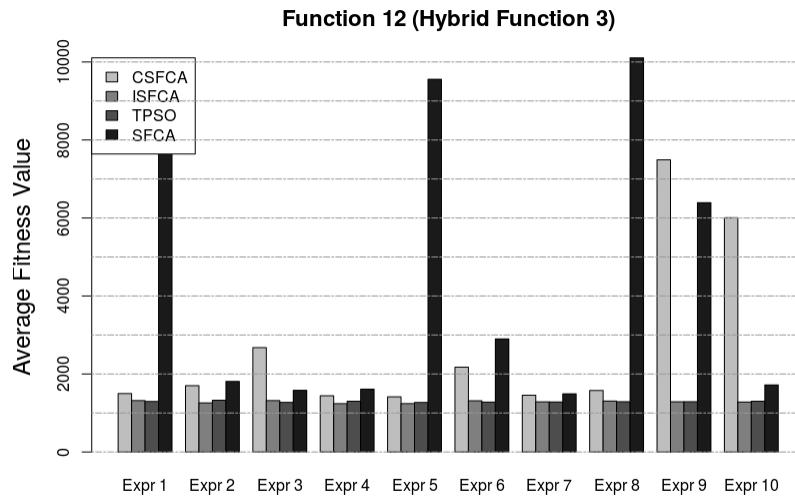


Figure 6.23: Average fitness values for Function 12 with 10 dimensions

Table 6.24: function-12, dimension-30

	SFPSO	CSFEP	SFEP	TPSO
Median	2.262814E+03	2.093796E+03	8.098215E+07	2.280177E+03
Mean	2.317707E+03	3.578488E+07	1.123866E+08	2.392247E+03
Best	2.100877E+03	1.748342E+03	2.153439E+03	2.280177E+03
StdDev	2.430944E+02	7.154759E+07	1.253791E+08	1.588321E+02

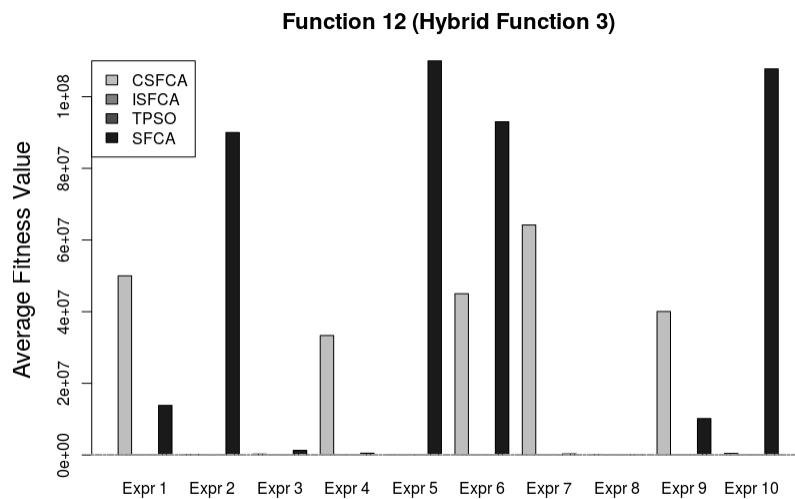


Figure 6.24: Average fitness values for Function 12 with 30 dimensions

6.13 Function 13: Composition Function 1

This function is improved moderately in both 10- and 30-diemsion cases. Table 6.25 and Figure 6.25 show that ISFCA and CSFCA improve the average fitness values for the 10-dimension case by 31% and 10% respectively. For the 30-dimension case, in Table 6.26 and 6.26, we can see that ISFCA and CSFCA improve the performance by 51% and 6% respectively.

Table 6.25: function-13, dimension-10

	SFPSO	CSFEP	SFEP	TPSO
Median	1.626676E+03	1.750040E+03	2.101426E+03	1.623272E+03
Mean	1.627982E+03	2.128914E+03	2.376883E+03	1.628781E+03
Best	1.622335E+03	1.635087E+03	1.676418E+03	1.618919E+03
StdDev	7.106025E+00	6.591729E+02	7.972695E+02	1.445686E+01

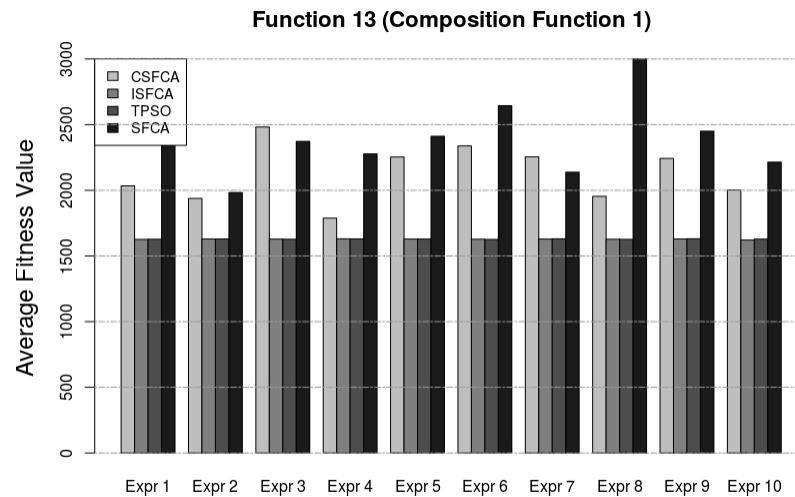


Figure 6.25: Average fitness values for Function 13 with 10 dimensions

Table 6.26: function-13, dimension-30

	SFPSO	CSFEP	SFEP	TPSO
Median	1.727952E+03	2.442454E+03	3.419566E+03	1.742700E+03
Mean	1.778258E+03	3.445463E+03	3.691270E+03	1.840829E+03
Best	1.723534E+03	1.740536E+03	2.380543E+03	1.732389E+03
StdDev	9.665278E+01	2.272010E+03	1.367277E+03	1.457157E+02

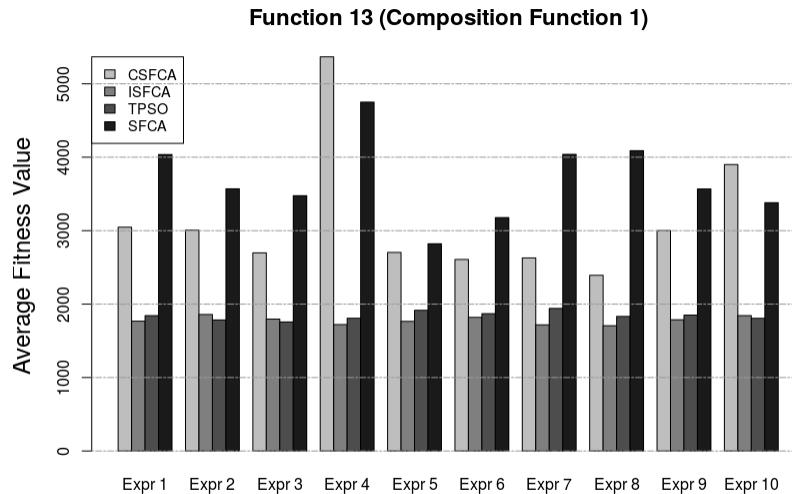


Figure 6.26: Average fitness values for Function 13 with 30 dimensions

6.14 Function 14: Composition Function 2

For this function, the improvement made by our approaches is trivial about 1% in the 10-dimension case. For the 30-dimension optimization, ISFCA and CSFCA improve the performance by 10% and 4% respectively.

Table 6.27: function-14, dimension-10

	SFPSO	CSFEP	SFEP	TPSO
Median	1.601795E+03	1.600173E+03	1.619095E+03	1.605406E+03
Mean	1.602429E+03	1.607129E+03	1.623200E+03	1.606235E+03
Best	1.601385E+03	1.591111E+03	1.597342E+03	1.604991E+03
StdDev	1.577398E+00	1.953208E+01	2.617243E+01	1.478468E+00

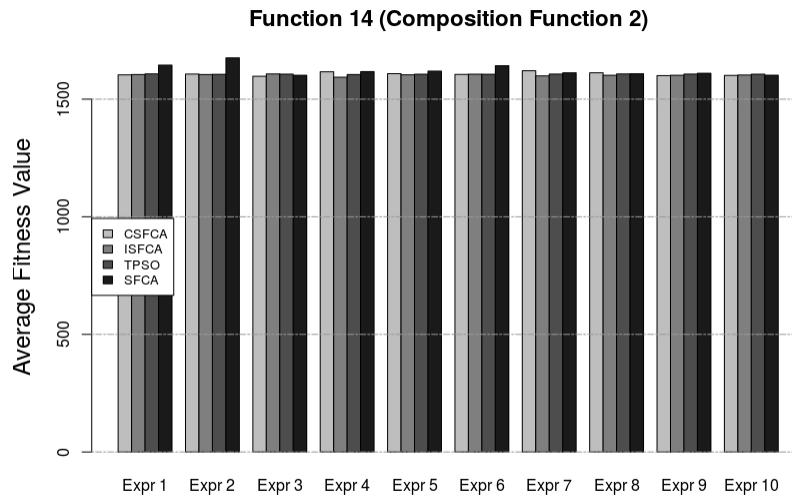


Figure 6.27: Average fitness values for Function 14 with 10 dimensions

Table 6.28: function-14, dimension-30

	SFPSO	CSFEP	SFEP	TPSO
Median	1.675847E+03	1.731879E+03	1.820677E+03	1.664094E+03
Mean	1.676279E+03	1.791878E+03	1.865010E+03	1.685711E+03
Best	1.646723E+03	1.660532E+03	1.693461E+03	1.658174E+03
StdDev	2.842502E+01	1.553106E+02	1.760265E+02	3.566090E+01

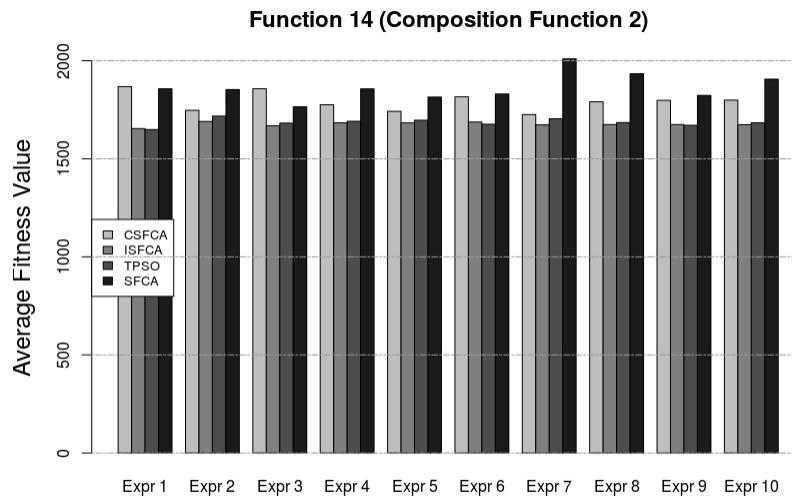


Figure 6.28: Average fitness values for Function 14 with 30 dimensions

6.15 Function 15: Composition Function 3

For this function, ISFCA works better than CSFCA. ISFCA improves the average fitness value by 20% and 29% for 10- and 30-dimension cases respectively. On the other hand, CSFCA produces improvement only by 1% and 16% for 10- and 30-dimension cases respectively.

Table 6.29: function-15, dimension-10

	SFPSO	CSFEP	SFEP	TPSO
Median	1.560743E+03	1.913027E+03	1.949996E+03	1.853726E+03
Mean	1.589476E+03	1.946018E+03	1.966892E+03	1.871080E+03
Best	1.525130E+03	1.871689E+03	1.855628E+03	1.772940E+03
StdDev	8.426385E+01	8.447839E+01	1.134500E+02	7.850262E+01

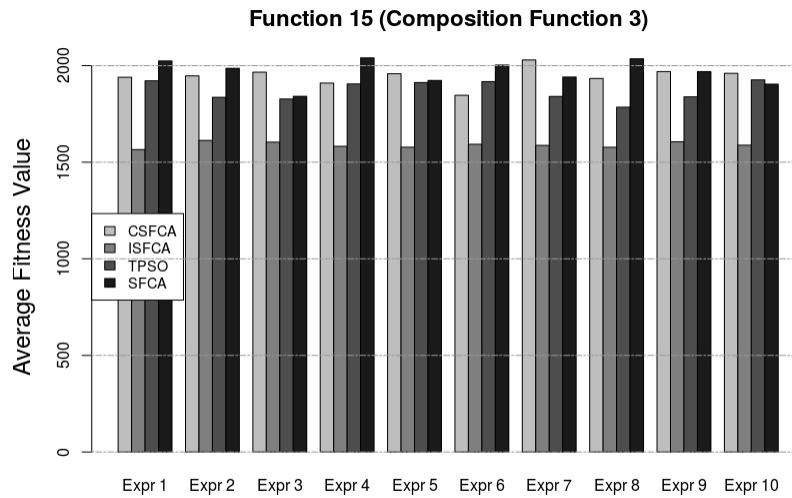


Figure 6.29: Average fitness values for Function 15 with 10 dimensions

Table 6.30: function-15, dimension-30

	SFPSO	CSFEP	SFEP	TPSO
Median	2.565830E+03	2.760375E+03	3.096788E+03	2.511983E+03
Mean	2.582142E+03	3.063021E+03	3.657078E+03	2.565208E+03
Best	2.498940E+03	2.227419E+03	3.055342E+03	2.504910E+03
StdDev	9.012990E+01	1.040607E+03	1.152769E+03	8.765290E+01

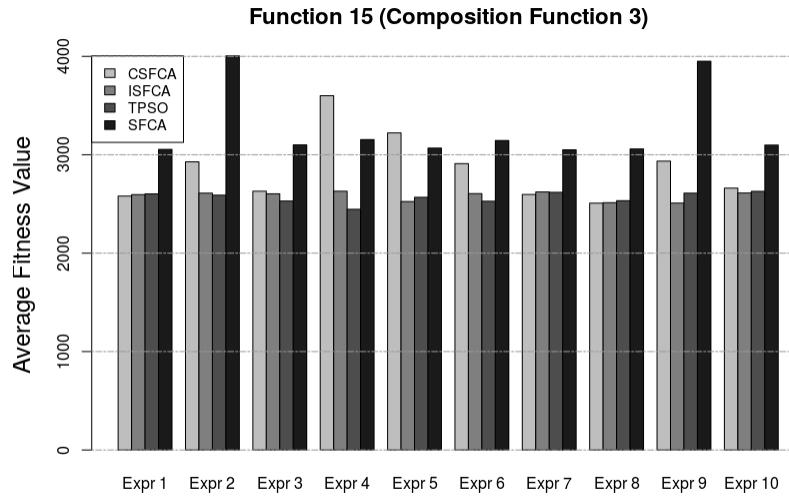


Figure 6.30: Average fitness values for Function 15 with 30 dimensions

6.16 Summary of Results

In this chapter, we presented an extensive comparison of our proposed approaches with the standard social fabric algorithm [Ali et al., 2016] and Tribe-PSO [Chen et al., 2006]. We chose these algorithms because both of them utilize multi-population and tribal strategies to improve the level of diversity in evolutionary algorithms.

As we can in the tables and figures for the functions 1, 2, 8, 10, and 12, the new neighborhood restructuring strategy and the confidence-based normative ranges generated more tan 50% improvement. It seems the proposed methods succeeded to help the individuals to avoid stagnation and local optima.

For the functions 4, 7, 11, 13, 14, and 15 the new approaches improve the performance with a lower percentage between 10% and 20%. Although, for the remaining functions the generated improvement is trivial. We hypothesize that it occurred because of the high-level complexity of the benchmark functions we used. In the standard implementation of the IEEE-CEC2015 library, the functions are twisted and rotated

to make it hard for optimization algorithms to get rid of local optima [Chen et al., 2014]. Also, as it is stated by above mentioned the No-Free Lunch Theorem, it is not expected for an optimization algorithm to work well on all of the possible functions [Wolpert and Macready, 1997].

Chapter 7

Conclusion and Future Work

7.1 Conclusion

In this thesis, two novel strategies were introduced to improve the robustness of CAs in both population and belief spaces. In the first strategy, a new neighborhood restructuring strategy is employed which aims at individuals with irregular and heterogeneous neighborhood structures. There is no centralized coordinator to control the topology of a population because the individuals are responsible for inspecting and modifying their neighborhood in a self-organized manner. Increasing the level of self-organization and autonomy is a key approach to improving robustness in a complex system. In the second strategy, the standard implementation of normative ranges in the belief space was replaced by the confidence intervals inspired from Inferential Statistics. The new knowledge source shows a more robust search behavior to fluctuations in the input data. Now, the size of normative ranges does not change dramatically with any temporal fluctuations.

For the new neighborhood restructuring, a fundamental assumption is that the individuals have to handle their interactions within a social network (fabric) infrastructure. Here, the social fabric is modeled using a dynamic graph which the neigh-

borhood size of the nodes (individuals) changes with time. This assumption implies another assumption that the interactions between agents occur locally. It means that the amount of influence which the individuals can receive from the other members is limited by their neighborhood size. In fact, this assumption is a key to avoiding immature convergence. As the agents are responsible for inspecting and modifying their neighborhood, the only limitation which we surmise when the size of a population increase, is the performance issues. Since the population is divided into some independent subpopulations (tribes), each tribe could be run in a separate thread. Running all the population in a single thread may pose a heavy burden on performance.

The second approach, confidence-based normative knowledge source, does not assume anything more than its standard version. It is entirely independent of the strategies deployed in the population space. In fact, the confidence-based approach could be utilized in the same framework as well as the standard method. So, it does not pose any additional limitations to the algorithm.

7.2 Future Work and Applications

The performance of both proposed approaches is assessed through a test-suite of 15 multi-modal and hybrid functions from IEEE-CEC2015. Both methods are compared to the original version of the social fabric based CA [Ali et al., 2016]. The results show improvement in most of the functions. In some of them, the results are quite promising.

We only tested our approaches against static functions, which means there is no change in the feedback from the environment. The improved robustness of the new methods makes them suitable to be utilized in dynamic problems like real-time applications where the algorithm needs to inspect and adapt itself to a changing environ-

ment continuously and as fast as possible [11]. The new neighborhood restructuring method allows the individuals to develop relationships in promising parts of the search space autonomously. The deployed inspect and adapt strategy makes it easy for the agents to change their point of focus and restructure themselves to find new optimum points in a non-stable search space. Also, the new update scheme for the normative ranges in the belief space can be considered suitable for such applications since it avoids deviation with any temporal change in the input data pattern.

With the growing industrial demands for data analytics, evolutionary algorithms could be the source of inspiration for the solutions to address such problems. The self-organization aspect of EAs makes them scalable to be used for analyzing datasets with a high level of complexity. [48], [34], and [42] are the examples which show promising results in social network analysis. They used EA methods such as GA, CA, and PSO for community detection and link prediction applications. [43] and [32] are the examples which proposed new approaches for data classification based on PSO and ACO. So, these research works have created a good background to use our proposed strategies for analytic applications.

Bibliography

- [1] M. Z. Ali and R. G. Reynolds. An intelligent social fabric influence component in cultural algorithms for knowledge learning in dynamic environments. In *2009 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology*, volume 2, pages 161–168, Sept 2009. doi: 10.1109/WI-IAT.2009.146.
- [2] Mostafa Z Ali. *Using cultural algorithms to solve optimization problems with a social fabric approach*. ProQuest, 2008.
- [3] Mostafa Z Ali, Robert G Reynolds, and Rose Ali. Enhancing cultural learning under environmental variability using layered heterogeneous sociometry-based networks. In *Web Intelligence and Intelligent Agent Technology (WI-IAT), 2010 IEEE/WIC/ACM International Conference on*, volume 2, pages 69–74. IEEE, 2010.
- [4] Mostafa Z Ali, Ayad M Salhieh, and Robert G Reynolds. Socio-cultural evolution via neighborhood-restructuring in intricate multi-layered networks. In *2012 IEEE Congress on Evolutionary Computation*, pages 1–8. IEEE, 2012.
- [5] Mostafa Z Ali, Ponnuthurai N Suganthan, Robert G Reynolds, and Amer F Al-Badarneh. Leveraged neighborhood restructuring in cultural algorithms for solving real-world numerical optimization problems. *IEEE transactions on evolutionary computation*, 20(2):218–231, 2016.

- [6] Md Asafuddoula, Tapabrata Ray, and Ruhul Sarker. An adaptive differential evolution algorithm and its performance on real world optimization problems. In *2011 IEEE Congress of Evolutionary Computation (CEC)*, pages 1057–1062. IEEE, 2011.
- [7] Christian Blum and Roderich Groß. Swarm intelligence in optimization and robotics. In *Springer Handbook of Computational Intelligence*, pages 1291–1309. Springer, 2015.
- [8] Eric Bonabeau, Marco Dorigo, and Guy Theraulaz. *Swarm intelligence: from natural to artificial systems*. Number 1. Oxford university press, 1999.
- [9] Daniel Bratton and James Kennedy. Defining a standard for particle swarm optimization. In *2007 IEEE swarm intelligence symposium*, pages 120–127. IEEE, 2007.
- [10] Edmund K Burke, Graham Kendall, et al. *Search methodologies*. Springer, 2005.
- [11] Xiangdong Che, Mostafa Ali, and Robert G Reynolds. Robust evolution optimization at the edge of chaos: Commercialization of culture algorithms. In *IEEE Congress on Evolutionary Computation*, pages 1–8. IEEE, 2010.
- [12] Kai Chen, Tonghua Li, and Tongcheng Cao. Tribe-psos: A novel global optimization algorithm and its application in molecular docking. *Chemometrics and intelligent laboratory systems*, 82(1):248–259, 2006.
- [13] Q Chen, B Liu, Q Zhang, JJ Liang, PN Suganthan, and BY Qu. Problem definitions and evaluation criteria for cec 2015 special session on bound constrained single-objective computationally expensive numerical optimization. Technical report, Technical Report, Computational Intelligence Laboratory, Zhengzhou University, Zhengzhou, 2014.

- [14] Li-Te Cheng, John Patterson, Steven L Rohall, Susanne Hupfer, and Steven Ross. Weaving a social fabric into existing software. In *Proceedings of the 4th international conference on Aspect-oriented software development*, pages 147–158. ACM, 2005.
- [15] Maurice Clerc and James Kennedy. The particle swarm-explosion, stability, and convergence in a multidimensional complex space. *IEEE transactions on Evolutionary Computation*, 6(1):58–73, 2002.
- [16] Marco A Montes De Oca, Jorge Peña, Thomas Stutzle, Carlo Pinciroli, and Marco Dorigo. Heterogeneous particle swarm optimizers. In *2009 IEEE Congress on Evolutionary Computation*, pages 698–705. IEEE, 2009.
- [17] William H Durham. *Coevolution: Genes, culture, and human diversity*. Stanford University Press, 1991.
- [18] Agoston E Eiben and James E Smith. *Introduction to evolutionary computing*, volume 53. Springer, 2003.
- [19] Saber M Elsayed, Ruhul A Sarker, and Daryl L Essam. Differential evolution with multiple strategies for solving cec2011 real-world numerical optimization problems. In *2011 IEEE Congress of Evolutionary Computation (CEC)*, pages 1041–1048. IEEE, 2011.
- [20] Yi-nan Guo, Jian Cheng, Yuan-yuan Cao, and Yong Lin. A novel multi-population cultural algorithm adopting knowledge migration. *Soft computing*, 15(5):897–905, 2011.
- [21] Xiaohui Hu, Russell C Eberhart, and Yuhui Shi. Engineering optimization with particle swarm. In *Swarm Intelligence Symposium, 2003. SIS’03. Proceedings of the 2003 IEEE*, pages 53–57. IEEE, 2003.

- [22] Hu Jianjun, Erik D Goodman, Kisung Seo, and Min Pei. Adaptive hierarchical fair competition (ahfc) model for parallel evolutionary algorithms. In *Proceedings of the Genetic and Evolutionary Computation Conference, New York*, pages 772–779, 2002.
- [23] Gareth Jones, Peter Willett, Robert C Glen, Andrew R Leach, and Robin Taylor. Development and validation of a genetic algorithm for flexible docking. *Journal of molecular biology*, 267(3):727–748, 1997.
- [24] J. Kennedy. Small worlds and mega-minds: effects of neighborhood topology on particle swarm performance. In *Proceedings of the 1999 Congress on Evolutionary Computation-CEC99 (Cat. No. 99TH8406)*, volume 3, page 1938 Vol. 3, 1999. doi: 10.1109/CEC.1999.785509.
- [25] James Kennedy. Bare bones particle swarms. In *Swarm Intelligence Symposium, 2003. SIS'03. Proceedings of the 2003 IEEE*, pages 80–87. IEEE, 2003.
- [26] James Kennedy, James F Kennedy, Russell C Eberhart, and Yuhui Shi. *Swarm intelligence*. Morgan Kaufmann, 2001.
- [27] Roger Lewin. *Complexity: Life at the edge of chaos*. University of Chicago Press, 1999.
- [28] Rui Mendes. *Population topologies and their influence in particle swarm performance*. PhD thesis, Citeseer, 2004.
- [29] Rui Mendes, James Kennedy, and José Neves. The fully informed particle swarm: simpler, maybe better. *IEEE transactions on evolutionary computation*, 8(3):204–210, 2004.
- [30] Marco A Montes de Oca and Thomas Stützle. Convergence behavior of the fully informed particle swarm optimization algorithm. In *Proceedings of the 10th*

- annual conference on Genetic and evolutionary computation*, pages 71–78. ACM, 2008.
- [31] Ronald W Morrison and Kenneth Alan De Jong. A test problem generator for non-stationary environments. In *Evolutionary Computation, 1999. CEC 99. Proceedings of the 1999 Congress on*, volume 3. IEEE, 1999.
 - [32] Fernando EB Otero, Alex A Freitas, and Colin G Johnson. Inducing decision trees with an ant colony optimization algorithm. *Applied Soft Computing*, 12(11):3615–3626, 2012.
 - [33] Bin Peng. Knowledge and population swarms in cultural algorithms for dynamic environments. 2005.
 - [34] Clara Pizzuti. Ga-net: A genetic algorithm for community detection in social networks. In *International Conference on Parallel Problem Solving from Nature*, pages 1081–1090. Springer, 2008.
 - [35] J Proakis. Probability, random variables and stochastic processes. *IEEE Transactions on Acoustics, Speech, and Signal Processing*, 33(6):1637–1637, 1985.
 - [36] M. R. Raeesi and Z. Kobti. Heterogeneous multi-population cultural algorithm. In *2013 IEEE Congress on Evolutionary Computation*, pages 292–299, June 2013. doi: 10.1109/CEC.2013.6557583.
 - [37] Robert G Reynolds. An introduction to cultural algorithms. In *Proceedings of the third annual conference on evolutionary programming*, volume 131139. Singapore, 1994.
 - [38] Robert G Reynolds and Mostafa Z Ali. Exploring knowledge and population swarms via an agent-based cultural algorithms simulation toolkit (cat). In *2007 IEEE Congress on Evolutionary Computation*, pages 2711–2718. IEEE, 2007.

- [39] Robert G Reynolds and Mostafa Z Ali. The social fabric approach as an approach to knowledge integration in cultural algorithms. In *2008 IEEE Congress on Evolutionary Computation (IEEE World Congress on Computational Intelligence)*, pages 4200–4207. IEEE, 2008.
- [40] Robert G Reynolds, Mostafa Ali, and Thaer Jayyousi. Mining the social fabric of archaic urban centers with cultural algorithms. *Computer*, 41(1):64–72, 2008.
- [41] Manisha Sharma, Manjaree Pandit, and Laxmi Srivastava. Reserve constrained multi-area economic dispatch employing differential evolution with time-varying mutation. *International journal of electrical power & energy systems*, 33(3):753–766, 2011.
- [42] Ehsan Sherkat, Maseud Rahgozar, and Masoud Asadpour. Structural link prediction based on ant colony approach in social networks. *Physica A: Statistical Mechanics and its Applications*, 419:80–94, 2015.
- [43] Tiago Sousa, Arlindo Silva, and Ana Neves. Particle swarm based data mining algorithms for classification tasks. *Parallel Computing*, 30(5):767–783, 2004.
- [44] Sara E Sterling. Aggregation techniques to characterize social networks. Technical report, DTIC Document, 2004.
- [45] Thomas Stützle. Ant colony optimization. In *International Conference on Evolutionary Multi-Criterion Optimization*, pages 2–2. Springer, 2009.
- [46] Massimiliano Vasile, Edmondo Minisci, and Marco Locatelli. An inflationary differential evolution algorithm for space trajectory optimization. *IEEE Transactions on Evolutionary Computation*, 15(2):267–281, 2011.
- [47] David H Wolpert and William G Macready. No free lunch theorems for optimization. *IEEE transactions on evolutionary computation*, 1(1):67–82, 1997.

- [48] Duan Xiaodong, Wang Cunrui, Liu Xiangdong, and Lin Yanping. Web community detection model using particle swarm optimization. In *2008 IEEE Congress on Evolutionary Computation (IEEE World Congress on Computational Intelligence)*, pages 1074–1079. IEEE, 2008.
- [49] Wei Xu, Lingbo Zhang, and Xingsheng Gu. A novel cultural algorithm and its application to the constrained optimization in ammonia synthesis. In *Life System Modeling and Intelligent Computing*, pages 52–58. Springer, 2010.
- [50] Wen Zhang, Yutian Liu, and Maurice Clerc. An adaptive pso algorithm for reactive power optimization. 2003.