

Evolving Heterogeneous Social Fabrics for the Solution of Real Valued Optimization Problems Using Cultural Algorithms

Robert G. Reynolds Yousof A. Gawasmeh

Department of Computer Science

Wayne State University

Detroit, Michigan 48202

Email: reynolds@cs.wayne.edu Email: ygawasmeh@wayne.edu

Abstract—A question of interest to those studying the emergence of social systems is the extent to which their organizational structure reflects the structures of the problems that are presented to them. In a recent study [14] used Cultural Algorithms as a framework in which to empirically address this and related questions. There, a problem generator based upon Langton's model of complexity was used to produce multi-dimensional real-valued problem landscapes of varying complexities. Various homogeneous social networks were then tested against the range of problems to see whether certain homogeneous networks were better at distributing problem solving knowledge from the Belief Space to individuals in the population. The experiments suggested that different network structures worked better in the distribution of knowledge for some optimization problems than others. If this is the case, then in a situation where several different problems are presented to a group, they may wish to utilize more than one network to solve them. In this paper, we investigate the advantages of utilizing a heterogeneous network over a suite of different problem. We show that heterogeneous approaches begin to dominate homogeneous ones as the problem complexity increases.

I. INTRODUCTION

One key question of interest to those studying the emergence of social systems is the extent to which their organizational structure reflects the structures of the problems that are presented to them. Specifically, does the structure of a social or organizational network facilitate the exchange of information needed by a group to solve a problem?

In a recent study [14] used Cultural Algorithms as a framework in which to empirically address this and related

questions. There, a problem generator based upon Langton's model of complexity was used to produce multi-dimensional real-valued problem landscapes of varying complexities. Various homogeneous social networks were then tested against the range of problems to see whether certain homogeneous networks were better at distributing problem solving knowledge from the Belief Space to individuals in the population.

The experiments suggested that different network structures worked better in the distribution of knowledge for some optimization problems than for others. If this is the case, then in a situation where several different problems are presented to a group, they may wish to utilize more than one network to solve them. In this paper, we investigate the advantages of utilizing a heterogeneous network over a suite of different problem.

II. THE CULTURAL ALGORITHMS FRAMEWORK

The Cultural Algorithm (CA) is an evolutionary computation model derived from conceptual models of the Cultural Evolutionary process [9] [10]. The population, belief space, and communication protocol between the population and the belief space are the three major components of this model, as shown in Fig. 1. The population can support any based computational model, such as Multi-Agent Systems, Genetic Algorithms, and evolutionary programming.

In the earliest Cultural Algorithm only one knowledge source (situational knowledge) was used [3]. Next, in [1], Reynolds and Saleem introduced other knowledge sources

into the belief space; situational, normative, topographic, domain, and finally history knowledge. The situational knowledge keeps track of the individual who did the best behavior in the population. The normative knowledge provides standards for individual behaviors to ensure that individual still within the scope of the system. The domain knowledge contains the sequence behaviors of the best individuals in the population. The history knowledge is useful in dynamic environment to store all changes in the problem landscape, such as the direction of the population behaviors either towards convergence or divergence. The topographical knowledge maintains a multi-dimensional grid representation of the population space to force the enhancing in the weak areas.

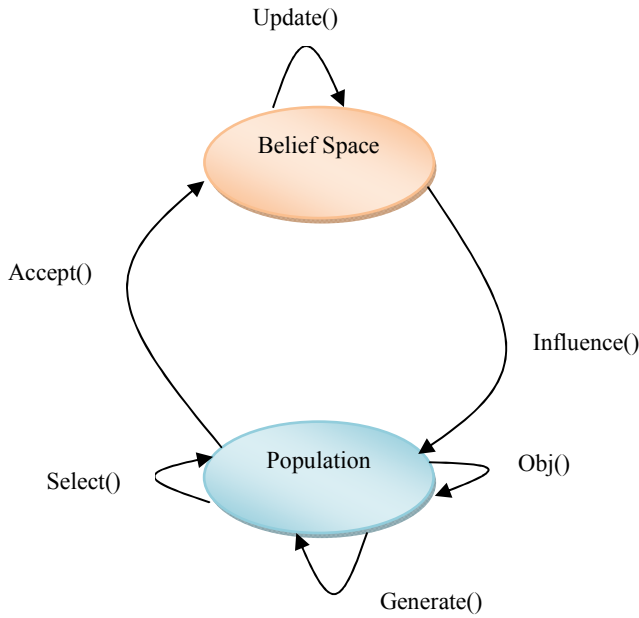


Figure 1. The Framework of Cultural Algorithms.

The basic pseudo-code of the Cultural Algorithm is shown in Fig. 2, where $P(t)$ represents the population at time t and $B(t)$ for the belief space at time t . At the end of each iteration, individuals in the population space are evaluated using the performance function, $Obj()$. Then the acceptance function, $accept()$, is used to select the appropriate individuals to update the Belief Space. The acceptance function selects the best elements to update, but in some cases the acceptance function selects from different categories to explore all results of the population. Updating the Belief Space occurs via the $update()$ function. In the Belief Space, there are many kinds of knowledge sources. Some sources are updated by the update function and some of them by the interaction with other updated sources. Next, the influence function transmits the knowledge from the belief space to the individuals in the population, $influence()$. The $accept()$ and $influence()$

functions form the communication protocol between the belief space and population.

The Cultural Algorithms repeatedly produces a new generation and update the belief space until the termination condition is satisfied. The Cultural Algorithms is flexible since it can run in short-term and long-term applications and in static and dynamic environments. The termination condition may depend on the population convergence or divergence. It may depend on constant and variable number of iterations.

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Begin
   $t=0$ ;
  Initiate  $B(t)$  and  $P(t)$ 
  Repeat
    Evaluate  $P(t)$  using  $Obj()$ 
    Update  $B(t)$  using  $Accept()$ 
    Generate  $P(t)$  using  $influence()$ 
     $t=t+1$ 
    Select  $P(t)$  from  $P(t-1)$ 
  Until (termination condition achieved)
End
  
```

Figure 2. Pseudo Code of Cultural Algorithms

III. THE SOCIAL FABRIC

Saleem [13] started integration of all knowledge sources into the Cultural Algorithm framework. He developed the CADE, the Cultural Algorithm for Dynamic Environment, to track the changes in the dynamic environment and store them in the Belief Space. He added the History and the Domain knowledge sources to the Belief Space. History knowledge allowed reasoning about time, while the Domain knowledge allowed reasoning about the individuals' direction and magnitude. He identified the required structure for each knowledge source in the Belief Space to find and track the changes in the dynamic environment.

Saleem's approach was applied to the solution of problems in the Cones World environment, where the problem was to find the highest peak in a multi-dimensional landscape, where the peaks are moving over time. The Cones World environment was generated via a benchmark problem generator developed by [6] and called DF1 in their work. Fig. 3 shows a 3D example of the Cones World environment. The random selection of the knowledge sources was the foundation of Saleem's integration function.

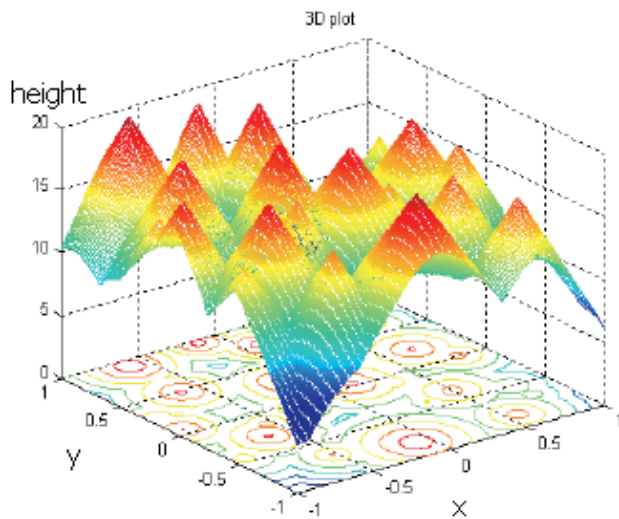


Figure 3. Example of cones world environment

Next, Peng [12] used the Marginal Value Theorem (MVT) [2] to integrate the knowledge sources of the Belief Space in order to guide the problem solving process. It had been shown in foraging theory that the Marginal Value Theorem can optimize the energy intake of predator/foragers within an environment. The main idea had been taken from ecology; the habitat resources would be decreased over time if the foragers resided too long within the habitat's borders. Thus, the forager stays within the habitat until the resources become less than the average expected value.

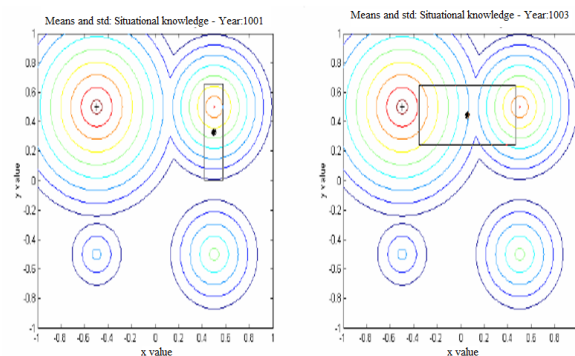


Figure 4. Situational at year 1000 and 1003

Peng observed at each time step that the individuals generated by each knowledge source using a normal distribution could be described by a “boundary box” or a patch with a given central tendency and standard deviation. For example, in Fig. 4 notice the shifting of the patch for situational knowledge from one place on the landscape to another. In fact, the original patch orientation is rotated and then translated towards the optimal point “+” over time by the knowledge source update process.

Each of the knowledge sources can be viewed as a predator. Each knowledge source (predator) controls the placement of individuals on the landscape to exploit the available resource (prey). If the average performance of those individuals controlled by knowledge source (predator) falls below the population average, the bounding box will be adjusted to increase the performance.

Peng modified the roulette wheel to emulate the action of the energy intake function. The size of a knowledge sources area under the wheel reflects its ability to exploit above population average gains. At every time step, each of the individuals in the population is influenced by one of the knowledge sources based upon the spin of the wheel. Then, the individual moves into the bounding box of the selected knowledge source.

In Pengs’ version, individuals acted independently and were influenced by a single knowledge source [12]. Ali [1] added the social fabric into the Cultural Algorithm framework to allow the interaction between the individuals so as to: give the individuals the ability of making decisions as to which knowledge source they will follow; identify the minimum social structure needed to solve problems of certain complexities; and investigate how the knowledge sources influence the individuals through a social network. Ali used a fixed topology to connect the individuals with their neighbors. The topology was kept constant throughout the optimization process, but the assigned to the network nodes were randomly reshuffled each time step.. Ali proved that just having a social fabric to distribute influence in the population space was sufficient to improve performance of the influence function in the Cultural algorithm.

Ali viewed the social fabric as a weaving process. The concept is illustrated schematically in Fig. 5. In the figure, there are five different networks where each is given as color-coded vertical lines, one for each of the five knowledge sources. Individuals are given as horizontal lines with a node representing a possible participation in each network. The node is blank, darkened, or darkened-circled. The node is blank if the individual does not participate in that particular network. It is darkened and colored the same color as the network if it participates sometimes. It is darkened-circled if it participates frequently. In the figure, the five individuals are ordered from highest participation to lowest participation of the five networks.

Ali’s main contribution was adding the social fabric into the Cultural Algorithm. The interconnections between the individuals in the population can be viewed as a social fabric, created by the interactions between the individual. Fig. 6 shows how the social fabric component is embedded into the Cultural Algorithm framework. In the figure there

are 5 knowledge sources: KS1, KS2, KS3, KS4, and KS5 that correspond to the five knowledge sources in the Belief Space. Every Knowledge source is color coded and its color is given to the individual that will be influence at that time step.

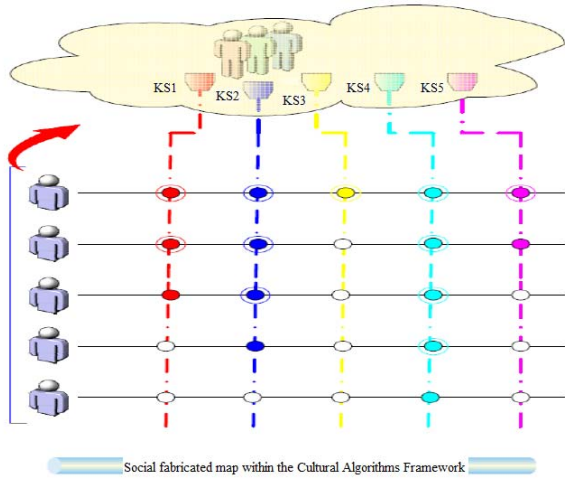


Figure 5. Social Fabric

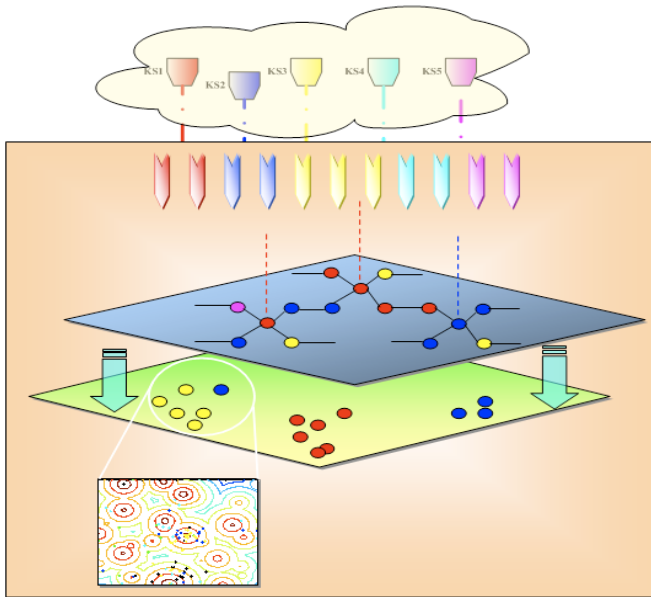


Figure 6. Embedded Social Fabric component in CAT

In Figure. 6, there are three perpendicular dotted lines point to three individuals with a complete set of neighbors. Each individual has four neighbors to interact with, so this topology named square topology. Ali used three other homogeneous topologies: Ring (lbest), Square, and Global (gbest) topologies[1]. Fig. 7 shows the three topologies. The topologies differ from each other by the number of neighbors connected to each individual or what called the degree.

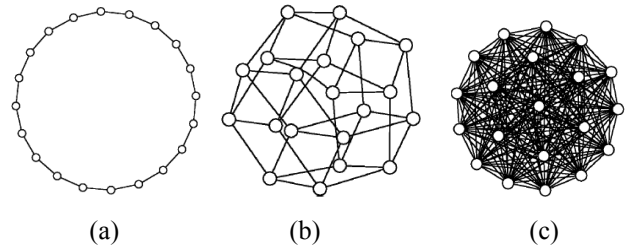


Figure 7. The three homogeneous topologies used in the Social Fabric model: (a) Ring topology. (b) Square topology. (c) Global topology

At each time step, every individual is influenced by one of the knowledge sources. Knowledge Sources do not know anything about the network and the selected individuals' position in it and vice versa. This is a double blind process. The individual then transmits the name of the influencing Knowledge Source to its neighbors through as many hops as specified. Next, each node counts up the number of Knowledge source bids that it collects. It will have the direct influence from the Knowledge Source that selected it, plus the ID's of the Knowledge Sources transmitted to it by its neighbors. The Knowledge Source that has the most votes is the winner and will direct the individual for that time step. This schema called majority winning schema" [11].

Other conflict resolution approaches are: direct, least frequently used, most frequently used, and random resolution. Suppose K is the knowledge source with the most votes from all the ones in individual's neighborhood, and L is the knowledge source from the belief space. In direct resolution, $K = L$. In LFU resolution, $K =$ the knowledge source recorded the least often from the beginning of the run. In MFU resolution, $K =$ the knowledge source recorded the most often from the beginning of the run. In random resolution, the resultant Knowledge Source is a randomly chosen one from the five knowledge sources.

Che [14] added three more homogeneous topologies to investigate in detail how a topology will impact the optimization performance: hexagon, octagon, and hexadecagon (16-gon). In the hexagon, every individual (node) interacts with exactly six neighbors see Fig. 8.a. Each individual in octagon communicates with eight neighbors see Fig. 8.b. In the 16-gon, each individual communicates with sixteen neighbors.

There are many ways to build the neighborhood topology [5][4][7]. Che gave each individual an ID. The IDs range was from 1 to n, where n is the population size. Each individual has m neighbors and marked with ID k, so the neighbors IDs will be $(n+k-m/2) \bmod n$, $(n+k-m/2 + 1) \bmod n$, ..., k, $(k+1) \bmod n$, $(k+2) \bmod n$, ..., $(k+m/2) \bmod n$. Octagon example is given in Fig. 9.

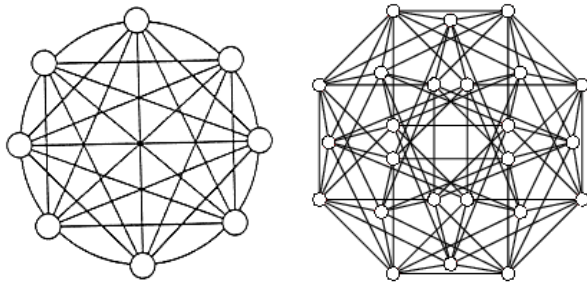


Figure 8. Hexagon and octagon topologies
a) Hexagon Topology b) Octagon Topology

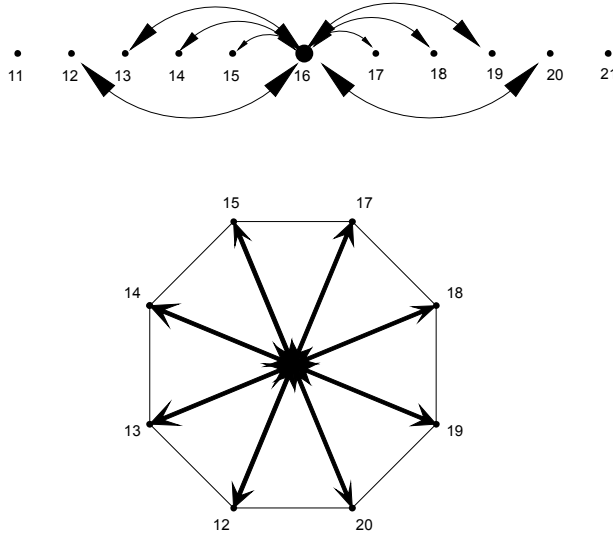


Figure 9. Octagon Neighborhood Topology Displayed in one dimension and two dimensions. [14]

Che [14] also employed a weighted incentive based majority win scheme. It is based on a Vector Voting model employed in the earliest version of Cultural Algorithms by Reynolds [9]. An example of weighted majority winning schema with octagon topology is given in Fig. 10. In the example, A0, A1... A7 and A8 are the individuals. A0 is the one deciding which knowledge source to follow. A1... A7 and A8 are the neighbors of agent A0. S, N, D, T, and H represent the situational, normative, domain, topographical, and history knowledge respectively. From Fig. 10, Agent A has the following votes:

- Neighbors A1 and A6 voted for Situational knowledge S (S repeated 2 times).
- Neighbors A2, A4, and A8 voted for Normative knowledge N (N repeated 3 times).

- Belief Space and neighbor A7 voted for Domain knowledge D (D repeated 2 times).
- A3 voted for Topographical knowledge (T repeated 1 time).
- A5 voted for History knowledge H (H repeated 1 time).

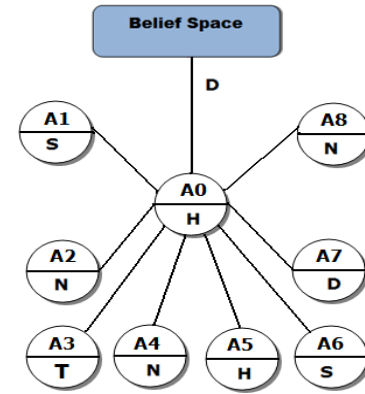


Figure 10. Knowledge Source Interaction in Population Level.

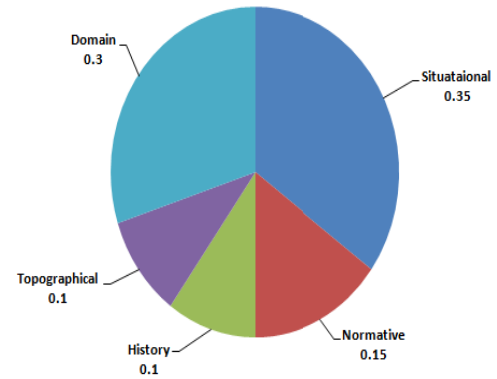


Figure 11. Current average fitness of each knowledge source.

In Peng's influence function, A0 will follow the knowledge source been selected by the belief space, so it would be the domain knowledge as shown in Fig. 10. The normative knowledge repeated the most (3 times), so A0 will follow it in Ali's influence function as shown in Fig. 12. Fig. 11 gives the average fitness of each knowledge source in the population space. Knowledge source fitness affects the individuals' making decision. In Che's influence function, A0 would follow the situational knowledge even if the normative knowledge occurred more frequently. The weighted majority win uses the knowledge sources as vectors in the vector voting approach. The average fitness of the current generation is the key to winning in this bidding game. If a less frequently used knowledge source finds a good solution its

average performance can increase noticeably and magnify its influence in the population space.

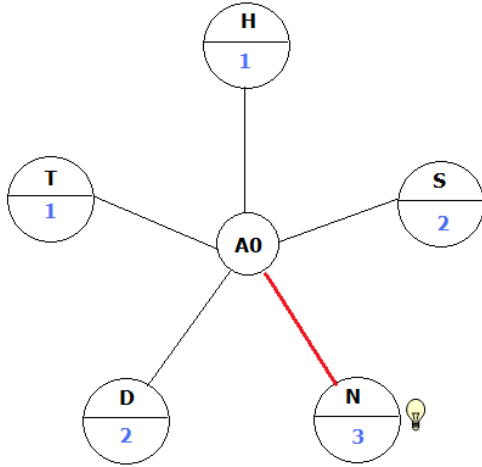


Figure 12. Un-weighted majority Win in Belief Space.

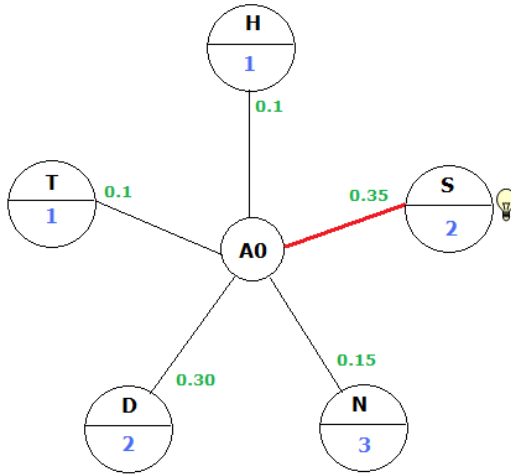


Figure 13. Weighted Majority Win in Belief Space.

IV. HETEROGENEOUS TOPOLOGY

In this section the mechanism for evolving the appropriate heterogeneous structure for a given problem is described. The approach uses the six homogeneous topologies (lbest, square, hexagon, octagon, hexa-decagon and global) that were used before with the social fabricated population space in CAT2.0, as shown in Fig. 14. In the previous system, CAT 2.0, a topology was selected to be used for the entire run as shown in step 1. Next in each generation the Knowledge source wheel is spun for each individual in order to select the knowledge source that will be the direct influence of that individual in that generation. The area under the wheel is the average performance of each KS for the previous generations. The direct influences are then distributed to the agents in step 3 along with the direct influences of its neighbors in the topology. Next, in step four the weighted majority conflict resolution rule is

used to determine which KS will actually influence the individual in that generation.

Fig. 15 demonstrates how the process has been changed for the new version. Step 1 reflects the selection of one of the fixed topologies for use in a generation based upon the previous performance of each topology using a roulette wheel approach. The area under the wheel for each topology is its normalized average performance in the previous generation. The selected topology is then embedded into the population space for that generation in step 2. Then for each topology there is a separate wheel shown in step 3 which is used to select the knowledge source used to influence each individual based upon the past performance of the knowledge sources for the selected topology. Thus, there are five separate KS wheels, one for each topology that is used for a generation. This wheel is used in step 4 to generate the direct influence for each individual in the population and collect the direct influence knowledge sources for its neighbors. In step 5 the weighted majority win conflict resolution rules is used to determine the winning KS for each individual. The individuals are then modified and evaluated. The results are used to update the selection wheels and the process starts again for the next generation.

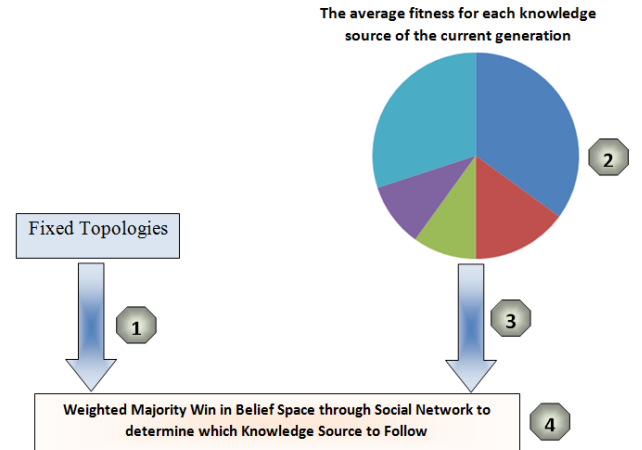


Figure 14. CAT2.0 topology model.

In this paper, we will use the Cones World to see how the heterogeneous social fabric can solve evolutionary problem and to compare our results with previous work used the same experiment environment. The evolutionary problems will be generated randomly of arbitrary complexities. Peng [8][12], Ali [1], and Che [14] used the Cones World before and therefore our results can be easily compared with theirs using this test bed.

Langton developed a model of a performance landscape described as a superimposed collection of cones, the Cones World. One of the parameters of the model Langton [5], A, value reflected the entropy of the system. Increasing A will lead to unpredictable system, In other word, A value

reflexes the system complexity. We picked $A = 1.01, 3.35$ and 3.99 for our test environment complexity. $A=1.01$ represents Fixed complexity class. The fixed complexity class will allow only the height on the cones to change. $A=3.35$ represents Periodic complexity class. The height and the slope of the cones will change together to make the Cones World more complicated. $A=3.99$ represents chaotic complexity classes and the system will be unpredictable. In this case, the height, slope, and the location of the cone will change over time making the landscape very dynamic and unpredictable.

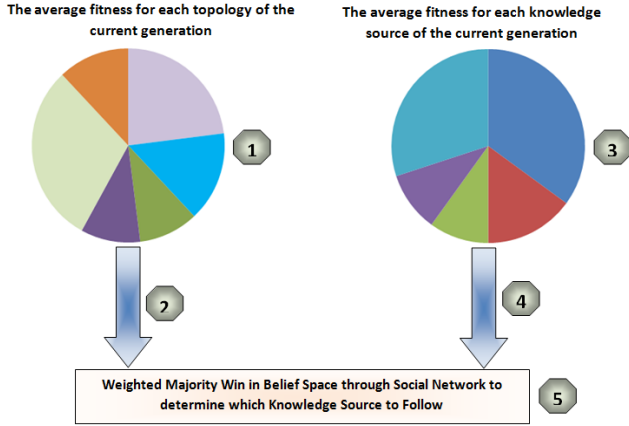


Figure 15. CAT 3.0 topology model.

V. RESULTS AND ANALYSIS

In this section we compare the use of heterogeneous topologies with the homogeneous topologies for the social fabric in terms of their relative performance and their effect on the knowledge sources within the three complexity categories (fixed, periodic, and chaotic categories).

Each Complexity ($1.01, 3.35, 3.99$) has five randomly generated example Landscapes. We use heterogeneous topology suite that consists of 6 Topologies: Lbest, Square, Hexagon, Octagon, Hexa-decagon, and Gbest. For each landscape/topology combination 10 runs were performed on each of the 5 landscapes. So each complexity has a total of 50 runs. The maximum number of generations for each run is 500.

For the fixed category of problems ($\alpha = 1.01$), Table I, the homogeneous topologies approach fared better than the heterogeneous approach. The heterogeneous topology had the fewest 58% number of solved problems, the greatest number of generation used on overall average, and the greatest standard deviation relative to the 50 runs. But the heterogeneous topology used the fewest number of generations in producing the solved problems, and the least maximum number of generations in producing the solved problems. So, for static problems with fixed cone distribution parameters the homogeneous topologies were the most effective in solving them. On the occasion that the

problem had features that supported the heterogeneous approach, that approach solved that problem effectively. However, the number of such problems constituted approximately 60% of the total number of runs.

TABLE I: THE PERFORMANCE COMPARISON OF THE SOCIAL FABRIC TOPOLOGY FOR $A = 1.01$

Topology	#ofTotalRuns	Overall Mean Generation Used	Std. Deviation	#of Runs w/ Solution Found	Minimum Generation Used	Runs w/ Solution Found Maximum Generation	Runs w/ Solution Found Mean Generation Used	Std. Deviation
lBest	50	224	168	38	11	339	137	72
square	50	213	152	42	9	358	158	93
Hexagon	50	229	169	40	40	491	161	112
Octagon	50	243	175	37	7	426	152	99
16-gon	50	219	160	41	44	477	158	100
global	50	238	186	35	10	361	126	83
Heterog	50	270	206	29	12	264	104	81

TABLE II: THE PERFORMANCE COMPARISON OF THE SOCIAL FABRIC TOPOLOGY FOR $A = 3.35$

Topology	#ofTotalRuns	Overall Mean Generation Used	Std. Deviation	#of Runs w/ Solution Found	Minimum Generation Used	Runs w/ Solution Found Maximum Generation	Runs w/ Solution Found Mean Generation Used	Std. Deviation
lBest	50	337	159	29	69	448	219	102
square	50	308	171	33	60	496	209	125
Hexagon	50	286	176	33	33	431	177	105
Octagon	50	243	168	39	22	489	170	110
16-gon	50	287	181	32	51	459	167	103
global	50	371	170	20	62	448	178	97
Heterog	50	203	177	42	6	477	146	131

For the periodic category of problems ($\alpha = 3.35$), Table II, the heterogeneous topology had the highest 84% number of solved problems and the lowest number of generations used in all 50 runs. It used the fewest number of generations in producing the solved problems. 6 generations used to produce one of the solved problems was the lowest number of generation of the three complexity classes. The octagon topology was the closest one to the heterogeneous' performance.

This class is characterized by the essential superposition of multiple static classes. Therefore, it makes sense that the heterogeneous approach that interweaves of subset of

homogeneous topologies will be a good fit for problems like this.

For the chaotic category of problems ($\alpha = 3.99$), Table III, the heterogeneous topology had the highest 74% number of solved problems and the lowest number of generations used in all 50 runs. It used the fewest number of generations in producing the solved problems. It had the minimum number of generation used to produce one of the solved problems. The standard deviation was the highest relative to the 50 runs and found solution runs. Thus, the heterogeneous topology is the fastest in solving the problems. The octagon and the global topologies were the closest one to the heterogeneous' performance.

VI. CONCLUSION

In this paper, we compared the heterogeneous topology with the homogeneous topologies. For static problems with predictable patterns of distribution, the homogeneous networks were the most effective. As more and more static problems were blended together to increase complexity, the heterogeneous approach became dominant. This was because there was work for more than one topology to perform. Our approach effectively allowed a team of networks to work on the problem space, each exploiting those patterns most suited for it. In future work we will examine exactly what properties attract the homogeneous networks to a distribution and how they can collaborate on a blended mix of distributions.

TABLE III: THE PERFORMANCE COMPARISON OF THE SOCIAL FABRIC TOPOLOGY FOR $A = 3.99$

Topology	#of TotalRuns	Overall Mean Generation Used	Std. Deviation	#of Runs w/ Solution Found	Minimum Generation Used	Runs w/ Solution Found Maximum Generation	Runs w/ Solution Found Mean Generation Used	Std. Deviation
lBest	50	301	159	35	83	487	216	107
square	50	302	160	35	54	464	217	112
Hexagon	50	300	163	33	34	481	197	95
Octagon	50	296	155	35	44	420	209	93
16-gon	50	291	172	34	10	441	193	113
global	50	289	172	33	38	400	181	99
Heterog	50	226	193	37	9	442	130	119

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