# Chapter 6

# CONCLUSION AND SCOPE FOR FUTURE WORK

*In this chapter, the conclusions of the thesis are stated and the scope for future research has been discussed.*
*In section 6.1, the concluding remarks are presented chapter wise and in section 6.2, the possible scope for future work has been stated.*

## 6.1. Concluding remarks

The research contributions and research achievements of this thesis are as follows:

**Chapter 1** provides the introduction, motivation and problem description for the present work including thesis scope/objectives, and contributions. Finally, the chapter concludes with the organization that describes the coverage of chapter in the thesis.

**Chapter 2** presents the theoretical background related to social network analysis. The section gives an overview of the metrics, community detection techniques, more specifically datasets and Application of community structures. The basic concepts of community detection techniques and problems in calculate the quality and accuracy of the community structures. Briefly discussed the state–of-art of community detection techniques used in used in various datasets and evolutionary algorithms etc. Further in the last section of the chapter application of community structures and evolution methodologies. Analysis of different community structures with the help various datasets and metric.

In **Chapter 3**, various traditional algorithms have been studied and this chapter focuses on improving the Genetic algorithm by incorporating a suitable prior knowledge of the evolutionary algorithms. We have presented opposition based learning concept (OBL) with genetic algorithm and modified the crossover operation. In whole experiment, we employed the matrix encoding for all the steps of the Genetic algorithm. In this chapter, we have been worked another concept related to the Genetic algorithm called as RGA (Regenerative Genetic Algorithm). In this experiment we replaced the mutation phase with the help of regeneration of the population. It not only maintains the diversity of the population but improves quality of the individuals and increases the percentage of best population selection for next iteration. We have calculated the community detection in social networks and find the quality and accuracy with the help of different type of metrics. Experimental analysis has been performed on the basis of various datasets and the value of the accuracy and quality based metrics. The results have been compared with existing methods i.e. basic Genetic algorithm (SGA), TGA, FN and GN with using Modularity (Q), Normalized mutual information (NMI), F-Measure and Adjusted Rand Index (ARI) and Number of Communities.

In **Chapter 4**, we have discussed the major drawbacks associated with Genetic algorithm include the problem of slow convergence rate and pre-assumption of the number of communities. To alleviate these issues, in this chapter, we have proposed three different hybrid-cascaded efficient frameworks of the genetic algorithm for both fuzzy community detection and crisp community detection. We used the simple modularity and fuzzy modularity formula for finding the quality of the detected communities with the various datasets. We compare the FGA (Fuzzy Genetic Algorithm) with existing SGA (Simple Genetic Algorithm) and node similarity based Genetic algorithm (VGA) with various metrics i.e. NMI,Coverage,Omega,Conductance, Entropy. After this we used another concept MCDM (Multiple Criteria Decision Making) it's generate the MCDM Rank with the help of quality and accuracy functions. In the next section of this chapter 4 is called the MGAFCD (Modified Genetic Algorithm for Community Detection). Experimental analysis has been performed on the basis of different size 10 datasets with Modularity function & compares with the existing methods i.e. MSFCM (Multi-client spectral FCM) AND GALS (Genetic Algorithm with local search for community detection). Hence In last section of the chapter, we have proposed NSGAP (Node Similarity based Genetic Algorithm with Permanence Concept). In this experiment we employed the both concept node similarity and permanence concept into the Genetic algorithm. We found both disjoint communities and fuzzy communities for the real world datasets & artificial datasets. In this proposed work, we used the well known datasets in the first step of this algorithm as a input after that generate the disjoint communities. In the next step, that disjoint communities are used as a input and generate the fuzzy community structure. Experimental analysis has been performed on the basis of Theta parameter and Accuracy value of all the datasets with metrics.  Proposed algorithm (NSGAP) compares the both fuzzy and disjoint communities on the same parameters. The new Genetic algorithm (NSGAP) is directly competing the GAFCD.

**In Chapter 5**, we have discussed the major issues associated with Genetic algorithm include the problem of slow convergence rate and pre-assumption of the number of communities. We have reduced the slow convergence rate problem with the help of some techniques but some issues are available. To alleviate these issues, in this chapter, we focused the Differential evolution algorithm for the community detection in social network. We choose DE because that is not required the prior information about the number of communities, so DE is very good approach for the real world datasets. We have proposed three different hybrid-combination and efficient frameworks of the Differential evolution algorithm for community detection in social networks. We employed the DE with Multiple objective functions, in this approach we replaced the Modularity fitness function instead of 7 other objective function i.e. Average degree; Normalized cut, internal density, Expansion, Conductance, cut ratio. We have analyzed the DE algorithm for the different datasets and various parameters. Main utilization of this experiment is that which version of DE is best for which type of dataset means small and large size. After my experiment we have found that the DE with Internal Density, average degree and expansion is good for the large and small datasets. In the next section, we have done another work DE with vertex similarity concept. In this work we analyzed the new version of the DE with artificial dataset and real world datasets for various parameter i.e. modularity and accuracy. We compare the proposed VSDE with existing DE algorithm called DECD and found that VSDE is better for quality wise and accuracy wise of all the datasets Further in the last section of the chapter, we proposed the DE with OBL (opposition based learning) and Tournament selection method for the community detection in social networks in various datasets and parameters. We compare the basic differential evolution algorithm (SDE) results with different versions of proposed DE algorithm i.e. TDE (Tournament based DE), OBDE (opposition learning based DE), TOBDE (Tournament and opposition learning based DE).To examine the efficacy and usefulness of proposed algorithms an appropriate qualitatively and quantitatively analysis using different type of metrics and various size of datasets. The obtained results justify the applicability of the proposed method.

Finally, the overall conclusion of the thesis is being summarized as follows: The works presents in the thesis, brings important contributions to social network analysis and complex networks domains. A detailed study of the literature was performed for all the research areas addressed in this thesis. The proposed methods and algorithms have been rigorously validated and compared with recent state-of-the-art methods. The contributions of this thesis are both theoretical and applicative.

## 6.2. Scope for Future Works

The research work presented in this thesis can be taken further into different directions. The scope for future works is as follows. We have done all proposed work in this thesis based on the Genetic algorithm and the Differential evolution algorithm.

Optimization is an important strategy for the solution of various research domains. The simplicity and efficiency of the GA algorithm are uncovered in experimental tests using artificial random networks and real-world dataset. The split intervals we choose after trial is 10 +20+20+50=100 as it gives the best value. It's my future research work. We want to use the split and regeneration technique both at the same time. The algorithm converges very quickly and the point of convergence is 70-75 while for the other algorithm it is around 90.This is because we used split runtime which result in the jumping of Q values when it moves from 1 split interval to another. As doing so the crossover and regeneration factor improves effectively which actually decreases when the number of iterations increases.

We will choose a fitness function according to requirement and find the optimized results. According to experiment, in further we will work on two important concepts i.e. first one is various other single point and multi-point based objective functions using with Differential evolution algorithm. Another one is we are going to apply the same concept to the different swarm techniques and advanced version of the DECD (Differential evolution based community detection) called CCDECD (co-operative co-evolutionary differential evolutionary based community detection).

Further work is on-going to maintain the desirable quality of community detection in social networks or complex network also. Furthermore, enhancement is required for improving the efficacy and accuracy of the proposed method by using some multidimensional optimization techniques in this work.