Implementation of Neural Network in Particle Swarm Optimization (PSO) Techniques

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***Abstract*— this paper describes different techniques of particle swam optimization (PSO), implementing feed-forward architecture in neural network. The algorithms for different types of optimization techniques are developed. These algorithms leads to optimum search solution to a given problem. The new position of the particle is calculated considering the best technique for PSO.**

Keywords- Genetic algorithm, Neural Network, Feed forward, Swarm intelligence, Swarm optimization

I. INTRODUCTION

A number of optimization algorithms have been developed in past decade by many researchers to solve complex problems. Some of the traditional optimizations are local and global optimization. To overcome the problem with these non traditional searching, new optimization algorithms were developed – genetic algorithm, tabu search, simulated annealing, scatter search, ant colony optimization and particle swarm optimization[1]. Genetic algorithm is a computerized search and optimization algorithms based on mechanics of natural genetics and natural selection. It is a biologically inspired search technique that exploits the survival of the fittest to find the optimal solution.

Feed forward is one of the methods in neural network that can be used to update the strength of the neurons in the network during training. Feed forward, Multilayer perceptrons are organized into different layers. The first layer is the input layer, followed by hidden layer that results into the output layer. Each individual is an aggregation of neurons. The individual's neurons contribute towards the optimum solution in the search space. The best search solutions are generated by this architecture.

Swarm intelligence (SI) is a type of artificial intelligence based on neurogenetic on the collective behaviour of decentralized, self-organized systems [2]. It is a new way of searching technique based on biological creatures in their natural habitat. Swarm describes behaviour of an aggregation (school) of animals of similar size and body orientation, generally cruising in the same direction. SI systems are typically made up of a population of simple agents interacting locally with one another and with their environment. The agents follow very simple rules, and although there is no centralized control structure dictating how individual agents should behave, local, and to a certain degree random, interactions between such agents lead to the emergence of "intelligent" global behavior, unknown to the individual agents.

II. PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) is the study of swarm intelligence, a stochastic population based technique for finding optimization problem in multidimensional search space [4]. It is originated from biological creatures: swarming of bees, schools of the fishes, queue of ants, flocks of birds, human crowds. Through these space simulations of various interpretations of the movement of organisms, often changing direction suddenly, scattering and regrouping, etc gives birth to a new era of searching technique called particle swarm optimization. All individuals in the swarm have the same behaviours and characteristics. It is assumed that information on the position and performance of particles can be exchanged during social interaction among particles in the neighbourhood. The particle coordinates with each other in the search space to get the best solution. Different structures are developed for information sharing process that leads to significant performance depending on the optimization problem.

III. PSO TECHNIQUES

A. LOCAL *best (lbest)*

The particle's best is found from each particle resulting in the local best. Fig 1, is a structural view of local best using feed forward multilayer perceptron. Circles represent particle or particle's search. Input layer contains individual particle. Hidden layer represents particle's searches. And the output layer depicts local best among individual particle. So the number of local best are same as number of particles.

ALGORITM 1 (LBEST)

1. Initialize the number of particles and other parameters
2. Initialize the position of other particles in search space
3. For i = 1 to n /* for n different particle */
4. For j = 1 to m /* for individual's search */
5. Search for x(i,j) best
6. next j
7. next i
8. if (moves in forward direction) /* calculate new position */
9. pi+1 = pi + rand() * x(i,j)
10. else (moves in backward direction)
11. pi+1 = pi-rand() * x(i,j)

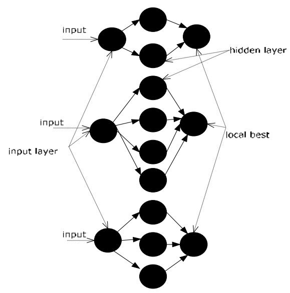

Fig. 1. Structural view of local best

B. Global best (gbest)

Search among all particles leads to global best. Particle's search is influenced by the best point found by any member of the entire population. The best particle acts as an attractor, pulling all the particles towards it. Eventually all particles search converge to one point [6]. Fig 2, is a structural view of global best. The algorithm leads to a global best.

ALGORITHM 2 (GBEST)

1. Same as Step -1 and 2 of Algorithm 1 (lbest)
2. For i = 1 to n (n number of particles)
3. Search x(i,j) best for x(i,j)/* best particle: leader */
4. next i
5. Same as Step 8 to 10 of Algo. 1 to calculate new position

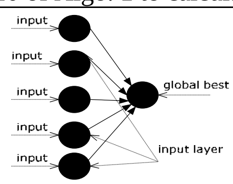

Fig. 2. Structural view of global best

C. Semi Hybrid best (shbest)

It is the hybrid of local and global optimization technique. First the local best is found and then the global best among it is found resulting in semi hybrid best. Fig 3, is a structural representation of semi hybrid best. The algorithm for semi hybrid best search.

ALGORITHM 3 (SHBEST)

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1.   Same as Step -1 and 2 of Algo. 1
2.   For i = 1 to n  /*for n different particle*/
3.      For j  = 1 to m /* for  individual's search*/
4.          Search for x(i,j) best  /*local best */
5.      next j
6.   next i
7.   For each x(i)
8.       Search for best /*global best*/
9.   next x(i)
10.  Converge to one solution /* the best among all */
11.  Same as Step 8-10 of Algo.  1 to calculate new position
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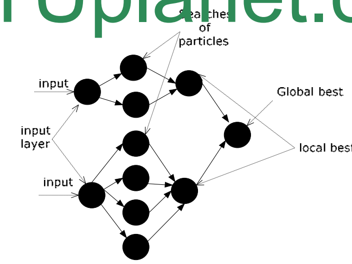

Fig. 3. Structural view of semi hybrid best

D. Overlap Hybrid best (ohbest)

For some particle, the search is common. The search is overlapped. Global best is found among all particles, resulting in hybrid best. The algorithm is same as hybrid best. Fig4 shows structural view of overlap best

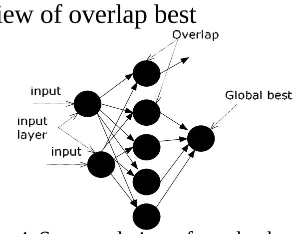

Fig. 4. Structural view of overlap best

IV. CONCLUSION

An alternative to existing search technique is population-based space search method. Particle swarm optimization techniques can rapidly search complex problems. The standard gbest, lbest are modified and shbest and ohbest techniques are proposed which are efficient for space search problems. PSO approaches share information about a best solution found by the swarm or a neighborhood of particles.

Sharing this information introduces a bias in the swarm's search, forcing it to converge on a single solution. When the influence of a current best solution is removed, each particle traverses the search space individually. PSO algorithm was proposed to mimic behaviors of social animals more closely through both social interaction and environmental interaction. In this study, we investigated different PSO algorithm on search optimization and its comparison.

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