Role of Optimization Techniques in Engineering

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ABSTRACT
By virtue of Optimization one can minimize or maximize a particular function in a finite dimensional Euclidean space over a subset of that space, which is generally determined by functional inequalities. It is the result of continuous research that Optimization has been evolve into an established field and had expanded in many branches like linear conic optimization, convex optimization, global optimization, discrete optimization, etc. Each of such branches has a sound theoretical foundation and is featured by an extensive collection of sophisticated algorithms and software. Optimization, as a powerful modeling and problem solving methodology, has a broad range of applications in management science, industry and engineering.

The main concern of optimized design is the finding of optimum parameters according to a given optimality standard. To cope up with the current development in engineering and other fields we must have to update over optimization techniques which can be use for the non-differentiable, not continuous objective functions. Every optimization techniques have its own merits and demerits and may be good for any particular purpose and may be worst for some other purpose. Like application of global optimization algorithm is sometimes a very time consuming task. The best local optimization methods for this purpose are the gradient methods. So in this work an intelligent way of using these optimization techniques is being presented which illustrate the fact that which techniques or a combination of techniques may be efficiently used for a given purpose. For that we have demonstrated the use of global optimization in two different tasks one is optimization of step size of LMS algorithm using Ant Colony Optimization (ACO) & Particle swarm optimization (PSO) and the other is designing of an Analog Sallen Key Band Pass filter using ACO.

Simulation of each case using MATLAB is done to prove the validity of optimized result and optimized designing.

Keywords
Optimization, Global Optimization Techniques, Ant Colony Optimization, Particle Swan Optimization, Sallen key band pass filter.

1. INTRODUCTION
Optimization is an intrinsic component of all engineering Felid. For the designing of any filter or for any other system or any algorithm the estimation of the coefficient or the variable is very important and they should be designed and built optimally and thrifty as much as the given conditions allow. Mathematically, a number of such optimization problems can be reduced to global minimization of multimodal functions. Such problems are difficult in the sense of algorithmic complexity, and global optimization algorithms are computationally very expensive. Aim of this paper is to review the capabilities and application possibilities of different global optimization algorithms as well as techniques in engineering practice.

Here use of two different global optimization techniques is demonstrated for two different problems of engineering and deterministic and stochastic global optimization algorithms without/and including some heuristic information on the problem are compared.

2. GLOBAL OPTIMIZATION TECHNIQUES

2.1 ACO
Let's start with an example to understand ACO. In fig. 1, a replica of an ant nest is shown. Here it may be observed that the first ant wanders randomly in the search of food source and ultimately reaches at food sources (f1, f2), then it returns to the nest (N), laying a pheromone trail. Other ants follow one of the paths at random, also laying pheromone trails. Since the ants on the shortest path lay pheromone trails faster, this path gets reinforced with more pheromone, making it more appealing to future ants. The ants become increasingly likely to follow the shortest path since it is constantly reinforced with a larger amount of pheromones. The pheromone trails of the longer paths evaporate.

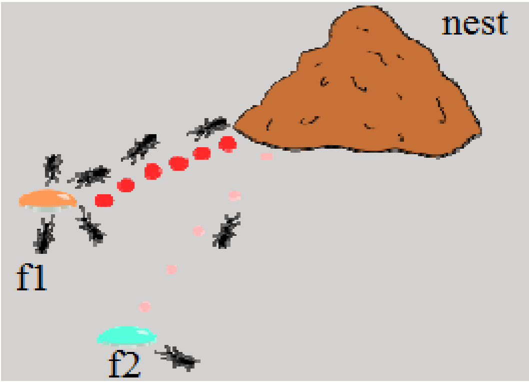

Fig. 1: Behavior of Ants during the search of food source

So this behavior of ant colonies had been transform in an algorithm for the solution of optimization problems of various fields. For this an analogy has been given in between the parameters of ant colony and that of algorithm. Following table illustrate that fact.

Table 1. Analogy between two systems

Natural terms	Terms for use in algorithm
Natural territory	graph (nodes and edges)
food source and nest	start and destination nodes
ants	our artificial ants
visibility	the reciprocal of distance

pheromones	artificial pheromones
oraging behavior	Random walk through graph (guided by pheromones)

With the help of this analogy we develop the algorithm for the given task.

2.2 PSO

For the better understanding of PSO let's have a look at fig. 2, in this figure two fishermen are in search of fish. As usually, the big fish is difficult to catch, hidden in the deepest part of the pond. At each time step, each fisherman tells to the other how deep the pond is at his placeAt the very beginning, as the depths are quite similar, they both follow their own ways.

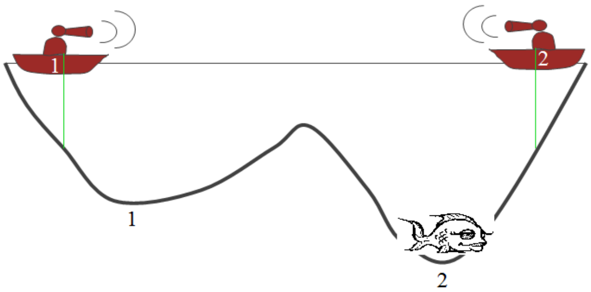

Fig. 2: Illustrative example of the PSO

Now, Fisherman 2 seems to be on a better place, so Fisherman 1 tends to go towards him quite rapidly. Now, the decision is a bit more difficult to make. On the one hand Fisherman 2 is still on a better place, but on the other hand, Fisherman 1's position is worse than before. So Fisherman 1 comes to a compromise: he still goes towards Fisherman 2, but more slowly than before. As we can see, doing that, he escapes from the local minimum.

- Thus we may conclude from that
- Each particle is searching for the optimum
- Each particle is moving and hence has a velocity.
- Each particle remembers the position it was in where it had its best result so far (its personal best)
- But this would not be much good on its own; particles need help in figuring out where to search.
- The particles in the swarm co-operate. They exchange information about what they've discovered in the places they have visited

3. USE OF OPTIMIZATION TECHNIQUES FOR OPTIMIZATION PROBLEMS

For solving global minimization problems we are having two different methods one is heuristic in which the global minimum is find with high probability, and in the second methods there is a guarantee of finding a global minimum with accuracy. Stochastic methods are one of the important classof heuristic methods in which number of techniques like simulated annealing and geneticalgorithms are derived from the fauna for finding the global optimum.

The mostimportant class of the second type of global optimization arebranch and bound methods. They derivetheir origin from combinatorial optimization, where global optima are also wanted but thevariables are discrete and take a few values only. This methodassures the finding of global minima with a desired accuracy after a knowable (though often exponential)number of steps. The basic idea behind this algorithm is that the configuration space is split recursively bybranching into smaller and smaller parts. This is not done uniformly, instead some parts arepreferred and others are eliminated. The details depend on bounding procedures. Lowerbounds on the objective allow toeliminate large portions of the configuration space early inthe computation so that only a (usually small) part of the branching tree has to be generatedand processed. The lower bounds may be obtained by using techniques of interval analysis, or other method. The interval global optimization method is: very stabile, robust anduniversally applicable. The interval algorithm guarantees that all stationary global solutionshave been found. Unfortunately this algorithm is sometimes very time consuming.

And on the other hand gradient based optimization methods are usually much faster. So here we can combine these both methods to get benefitted by the advantage of both optimization techniques. For this, first local minimum is foundusing a local optimization method, and then we check if this minimum is global using thealgorithm of interval global optimization.

3.1 A local optimization method

The LMS algorithm is by far the most widely used algorithm for this type of optimization problems because of its simplicity, confirmation of convergence in stationary environment and stable behavior.

The optimal solution for the parameters of the adaptive filter implementedthrough a linear combiner, which corresponds to the case of multiple input signals. This solution leadsto the minimum mean-square error in estimating the reference signal $d(k)$. The optimal (Wiener)solution is given by

$$w_0 = R^{-1}p \quad (1)$$

whereR = $E[x(k)x^T(k)]$ and p = $E[d(k)x(k)]$, assuming that $d(k)$ and $x(k)$ are jointly wide-sense stationary.

If good estimates of matrix R, denoted by $\hat{R}(k)$, and of vector p, denoted by $\hat{p}(k)$, are available,steepest-descent-based algorithm can be used to search the solution of equation (1) asfollows:

$$W(k+1)=w(k)-\mu\widehat{g_w}(k)$$

$$=w(k)+2\mu(\hat{p}(k)-\hat{R}(k)w(k)) \quad (2)$$

for$k = 0, 1, 2, \ldots$, where$\widehat{g_w}(k)$ represents an estimate of the gradient vector of the objectivefunction with respect to the filter coefficients.

One possible solution is to estimate the gradient vector by employing instantaneous estimates for Rand p as follows:

$$\hat{R}(k) = x(k)x^T(k)$$

$$\hat{p}(k) = d(k)x(k) \quad (3)$$

The resulting gradient estimate is given by

$$\widehat{g_w}(k) = -2d(k)x(k) + 2x(k)x^T(k)w(k)$$

$$= 2x(k)(-d(k) + x^T(k)w(k))$$

$$= -2e(k)x(k) \quad (4)$$

Note that if the objective function is replaced by the instantaneous square error $e^2(k)$, instead of theMSE, the above gradient estimate represents the true gradient vector since

$$\frac{\partial e^2(k)}{\partial w} = \left(2e(k)\frac{\partial e(k)}{\partial w_0}\ 2e(k)\frac{\partial e(k)}{\partial w_1} \ldots 2e(k)\frac{\partial e(k)}{\partial w_N}\right)^T$$

$$= -2e(k)x(k)$$

$$= \widehat{g_w}(k) \qquad (5)$$

The resulting gradient-based algorithm is known as the least-mean-square (LMS) algorithm, whoseupdating equation is

$$w(k+1) = w(k) + 2\mu e(k)x(k) \qquad (6)$$

Where the convergence factor μ, should be chosen in a range to guarantee convergence.

3.2 Purposed approach

This task will be accomplished by the above discussed global optimization techniques. For this purpose we have use the analogy discussed in the table 1 to write the program and find the value of μ for different value of alpha α. Both the optimization techniques (ACO, PSO) are used for this purpose. And the results are shown in fig 3. It may be clearly observed from this graph that the value of μ is minimum for the maximum value of α.

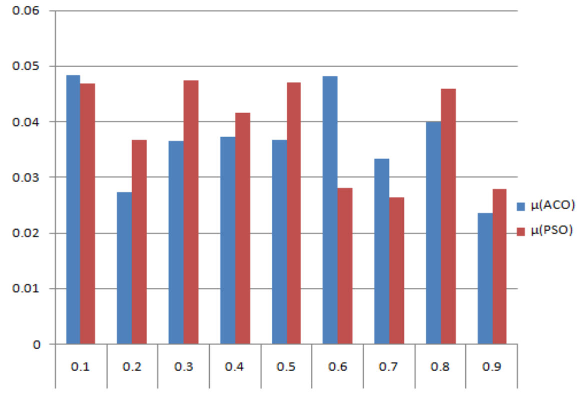

Fig. 3: Calculation of μ using ACO & PSO

Now these values of μ may be use to calculate the minimum mean square error (MMSE) which is required for the system identification. This task is also accomplished by using the same analogy discussed in the table 1.

From the graph presented in fig 4,5 it is apparent that the value of MMSE can be efficiently evaluated by using these optimization techniques. One important observation from the chart is that the values of MMSE are approximately similar for both the optimization techniques, although the values evaluated using PSO are more uniform and shows that we will get the minimum MMSE for minimum values of μ. The area under red circle clearly depicts this fact.

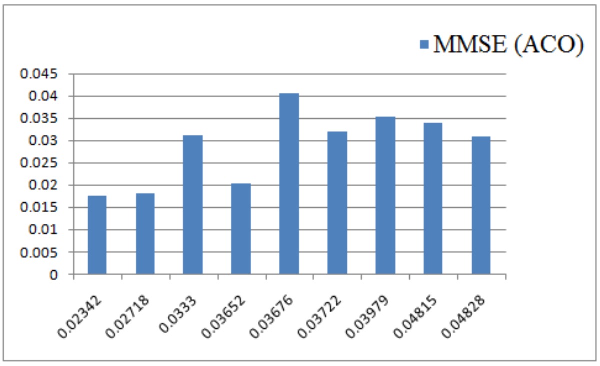

Fig. 4: μ vs MMSE while ACO is used as a optimization techniques

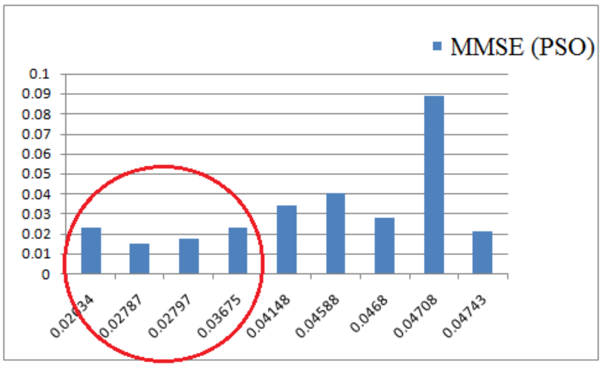

Fig.5: μ vs MMSE while ACO is used as a optimization techniques

4. APPLICATION TO THE OPTIMAL DESIGN OF THE SALLEN KEY BAND PASS FILTER

We have seen the use of optimization techniques for the improvement of LMS algorithm. In this section we will emphasize on some design aspects and will design a band pass filter shown in fig 6.

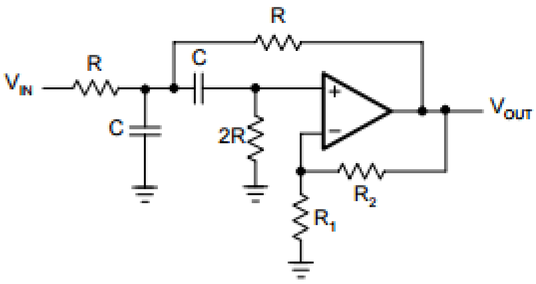

Fig.6: Second Order Sallen-Key Band-pass filter with Gain A>1

The standard transfer function of this filter may be written as

$$H(S) = \frac{SA(\omega_0/Q)}{S^2 + \left(\frac{\omega_0}{Q}\right)S + \omega_0^2}$$

Let the design components be

C = 10nF, R3 = 10k, R4 = 10k, f_o = 15kHz

R = 1/ (2π × 15000 × 10 × 10^{-9}) = 1.06k

G = 1 + (10/10) = 2

A = 2/ (3 - 2) = 2

Q = 1/ (3 – 2) = 1

Bandwidth = f_o/Q = 15 kHz/ 1 = 15 kHz

After putting all these values the transfer function may further be modified as:

$$H(S)=\frac{188520S}{S^2+94260S+8.8e09}$$

We can vary the Quality factor by varying the gain G through the resistor R4 or R3. In this we have fix the R3 at 10k, and varies R4. Thus, we will get the different values of Q for the following values of R4 = 10k, 16k, 17.5k, 18.75k, 19k, 19.9k.

Table 2: Values of R4 and respective Q

R4 (kΩ)	10	16	17.5	18.75	19	19.9
Q	1.0	2.5	4	8	10	100

By using the transfer function, the frequency response of the filter at varying Q's can be plotted using MATLAB to verify the design.The cutoff frequency (ω_L, ω_H) and the selectivity factor (Q1, Q2) of filter, which depend only on the values of the passives components For comparison reasons, the specification chosen here is:

Q1=0.7654

Q2=1.8478

The values of the resistors and capacitors to choose must be able to generate ω_L, ω_H, Q1and Q2 approaching the specified values. For this, define the Total Error (TE) which expresses the offset values, of the cut-off frequency and the selectivity factor, compared to the desired values, by:

$$TE = \alpha\Delta\omega + \beta\Delta Q$$

Where

$$\Delta\omega = \frac{|\omega_L - \omega| + |\omega_H - \omega|}{\omega}$$

$$\Delta Q = |Q_1 - \frac{1}{0.7654}| + |Q_2 - \frac{1}{0.8478}|$$

The objective function considered is the Total Error which is calculated for the different values of α and β. The decision variables are the resistors and capacitors forming the circuit.

4.1 Simulation results

In this section we have shown the simulation results of the optimized design when ACO is used as an optimization algorithm. MATLAB is used as a simulating tool and the values of different parameters are shown in table

Table 3: Values of components and related filter performances

SN	Alpha	Beta	C(pf)	R_4(K)	F_L(KHz)	F_H(KHz)	B.W. (KHz)	Q	F_O(KHz)
1	0.985	0.015	393.07	18.693	14.020	15.980	1.9598	7.6358	15.0
2	0.99	0.01	139.35	18.945	14.209	15.791	1.5829	9.4762	15.0
3	0.981	.009	223.92	18.995	14.246	15.754	1.5015	9.9500	15.0
4	0.9999	0.0001	850.75	19.899	14.925	15.075	150.7538	99.5	15.0
5	0.99985	0.00015	736.33	19.849	14.887	15.113	226.1307	66.33	15.0
6	0.99993	0.00007	194.07	19.899	14.925	15.075	150.7538	99.5	15.0
7	0.5	0.5	631.86	10	7.5	22.5	15	1	15.0
8	0.9	0.1	796.48	15.980	11.985	18.015	6.0302	2.4875	15.0
9	0.8	0.2	980.10	13.317	9.9875	20.013	10.025	1.496	15.0

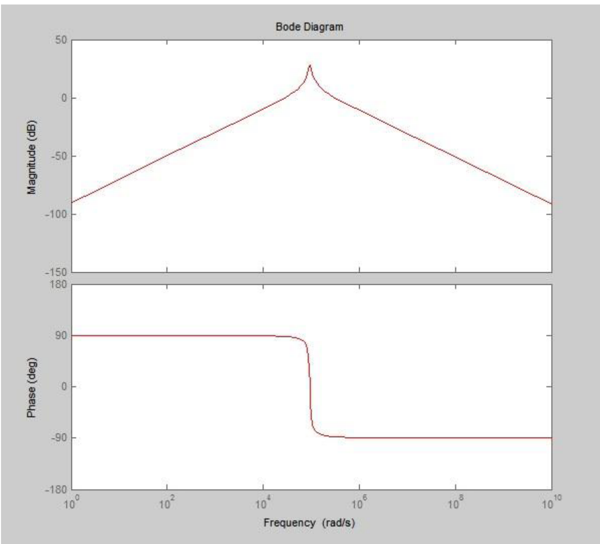

Fig. 7: Simulation of ACO1.

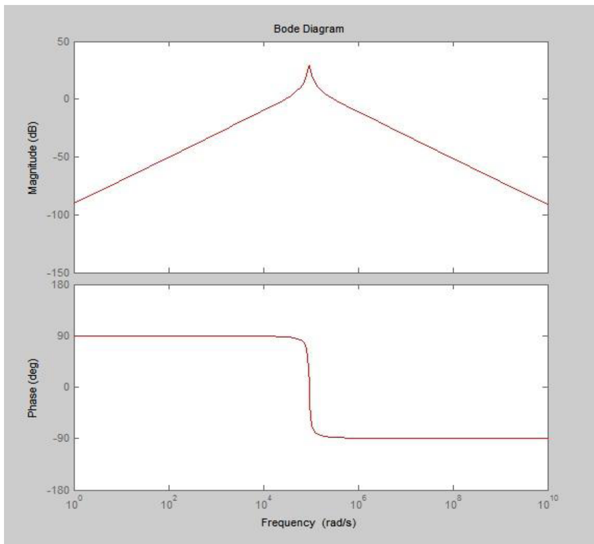

Fig. 8: Simulation of ACO 2.

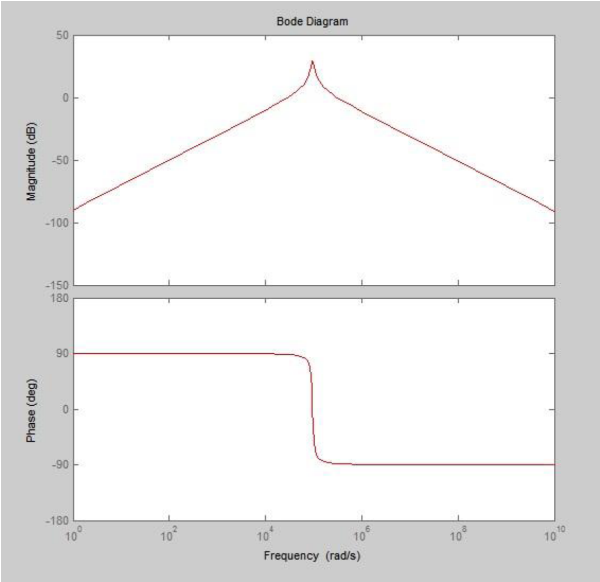

Fig. 9: Simulation of ACO 3.

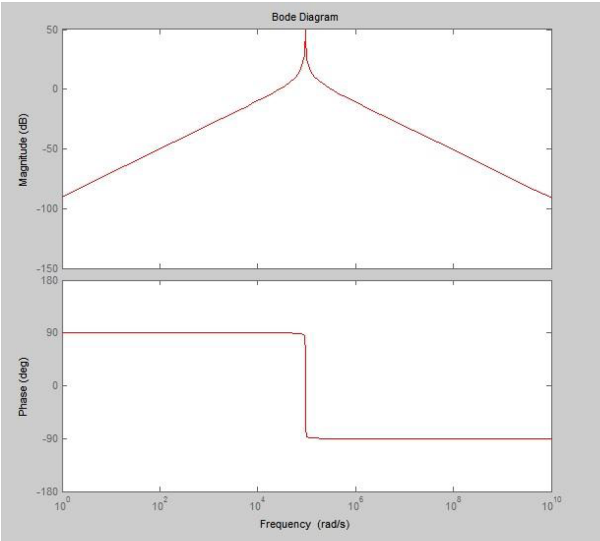

Fig. 10: Simulation of ACO 4.

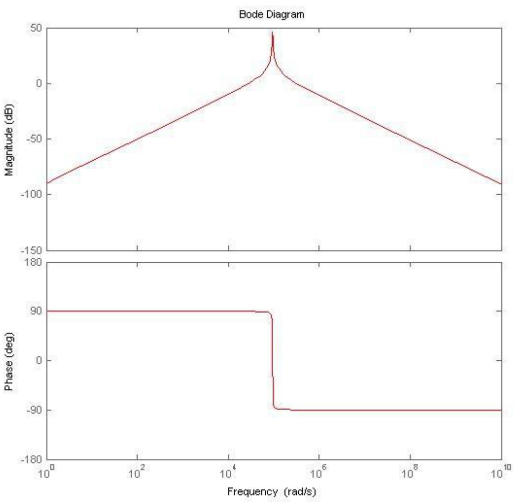

Fig. 11: Simulation of ACO 5.

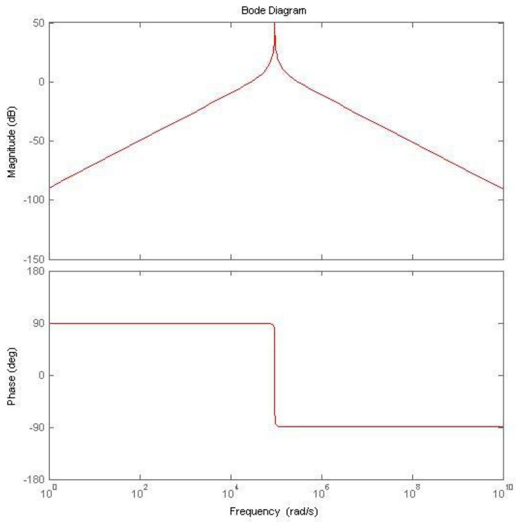

Fig. 12: Simulation of ACO 6.

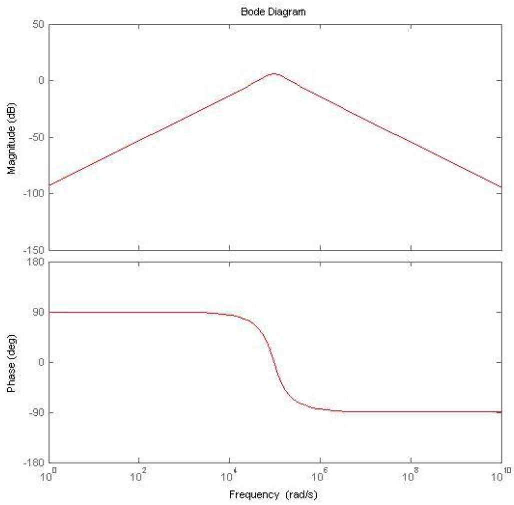

Fig. 13: Simulation of ACO7.

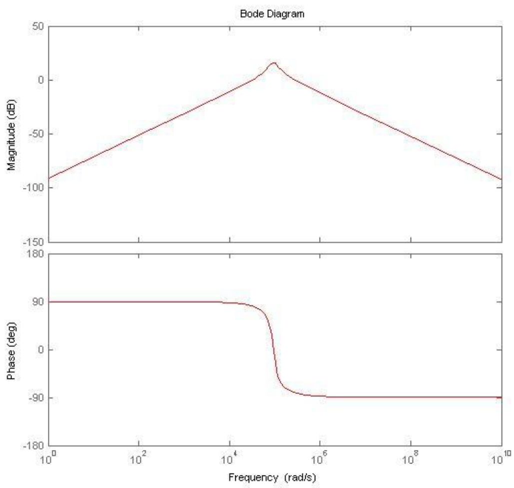

Fig. 14: Simulation of ACO 8.

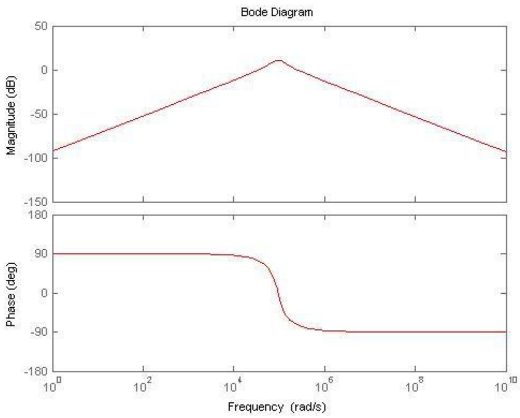

Fig. 15: Simulation of ACO 9.

5. CONCLUSION

In this work two different optimization techniques (ACO, PSO) were employed for two different types of problems. From the simulation results and above analysis we may conclude that each optimization techniques is having its own advantages, and may be used individually or with combination of other algorithm for providing better results for a given task. As in the case of optimization problem we have combined ACO, PSO with LMS algorithm and found that the performance of LMS algorithm were enhanced, further in the last section we have use ACO for calculating the parameters of a filter and find that the results were outstanding.

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