A NOVEL HYBRID SIMULATED ANNEALING –DIRECT SEARCH ALGORITHM FOR OPTIMUM SYNTHESIS OF FUNCTION GENERATION PROBLEM

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ABSTRACT:

This paper presents the results of a newly developed hybrid Simulated Annealing –Direct search Algorithm (SADS) for the optimization of mechanism synthesis for function generation problem and proposes a hybrid optimization method based on the fusion of the Simulated annealing (SA) and Rosenbrock Search (RS), derivative-free type method of optimization, in which the SA is embedded the RS to enhance its search capability. This algorithm combines the advantages of the global optimization technique and a classical non linear programming technique. A brief overview of hybrid SADS algorithm is presented and applied to dimensional synthesis of a planer four bar mechanism. The optimization is carried out to minimize the objective function formulated from the structural error at the accuracy points. A novel hybrid SADS is employed to determine the optimal values for the design variables that best satisfy the desired objectives of the problem. Simulation results demonstrate the remarkable advantages of our approach in achieving the diverse optimal solutions and improved converge speed. The applicability of this algorithm is illustrated by solving a nonlinear function generation problems and the method produce accurate and acceptable solution in all cases.

Keywords: *Function generation, simulated annealing, Rosenbrock Search, Hybrid algorithm, four bar mechanism*

1. INTRODUCTION:

In the past, a number of different techniques have been employed for the synthesis of mechanisms [1-4]. In the traditional approaches, the solution method is based on the graphical, and /or analytical design methods. Later with the proliferation of high speed computers and their integration into mechanism analysis and synthesis, a wide variety of numerical optimization methods have been developed for the synthesis of mechanisms. The graphical methods can provide a quick and easy method of design. But this approach has accuracy limitations. The analytical methods in practice today are mostly based on algebraic methods [5], displacement matrix method [6] or complex number methods [7]. In this approaches, the mechanism synthesis problem (MSP) is solved and carried out to satisfy accuracy points exactly. A major drawback in using the analytical methods is that there could be significant errors in the overall output between the precision points, branching and incorrect sequence of accuracy points and impractical for design and optimization of complex mechanism. Mechanism involving a finite number of links posses an inherent error and it is the task of the designer to reduce this error to a sufficiently low value. Many numerical optimizations [8, 9] are available at present for design optimization of engineering problems to find optimum design. Solving MSP can be complex and a time consuming process when there are large numbers of design variables and constraints. Hence there is a need for efficient and reliable algorithms that solves

such problems. It is known that no algorithm can surely find the absolute minimum in a polynomial time with number of variables, some very successful heuristic algorithms have been developed. Amongst these, the SA, method of Kirkpatrick has proven to very successful in a broad class of situations. In this paper, Hybrid SADS is developed and applied for the synthesis of a mechanism for the function generation problem. SA is a stochastic heuristic algorithm in which the solutions are searched in hill climbing process constantly commenced by random moves. Because of its ease use,SA is an extremely popular method for solving large-sized and practical problems.However,for various reasons, like many other search algorithms, SA may become trapped by any local minima, which doesn't allows moving up or down ,or take a long time to find a reasonable solution, which sometimes makes the method unreferrable. For this reason, many SA implementations have been done as a part of a hybrid method [10-17].

2. SIMULATED ANNEALING (SA)

2.1. Fundamental Concept:

SA [18, 19] is a generic probabilistic Meta–algorithm for the global optimization problem, namely locating a good approximation to the global optimum of a given function in a large search space. SA is based on an analogy to the cooling of heated metals. In any heated metal sample the probability of some cluster of atoms at a position, (r_i), exhibiting a specific energy, E (r_i), at some temperature T, is defined by the Boltzmann Probability factor:

$$P(E(r_i)) = e - [E(r_i) / k_B T] \quad (1)$$

Where k_B is Boltzmann's constant .As a metal is slowly cooled, atoms will fluctuate between relatively higher and lower energy levels and allowed to equilibrate at each temperature T. The material will approach a ground state, a highly ordered form in which there is a very little probability for the existence of a high energy state throughout the material. If the energy function of this physical system is replaced by an objective function, f (X), that is dependent on a vector of design variables, X, then the slow progression towards an ordered ground state is representative of a progression to a global optimum. To achieve this, a control temperature T, analogues to a temperature, and a constant C, analogues to k_B, must be specified for the optimization problem. In standard iterative improvement methods, a series of trial points is generated until an improvement in the objective function is noted in which case the trial point is accepted. However, this process only allows for downhill movements to be made over the domain. In order to generate the annealing behavior, a secondary criterion is added to the process. If a trial point generates a large value of objective function then the probability of accepting this trial point is determined using the Boltzmann Probability distribution:

$$P[\text{accept } X_t] = e - [f(x_t) - f(x_o) / CT] \quad (2)$$

Where X_o is the initial starting point. This probability is compared against a randomly generated number over the range [0 ….. 1]. If P [accept X_t] ≥ random [0….1] then the trial point is accepted. This dependence on random numbers makes a SA a stochastic method.

2.2. SA Algorithm:

The algorithm proceeds as follows:

Step1: Starting from the initial point X_0, the algorithm generates successively improved points X_1, X_2…… moving towards the global minimum solutions. The initial value of a control parameter (T) is suitably high and a methodology for de crementing (T) is applied.

Step2: A sequence of design vector is then generated until equilibrium is reached.

Step3: During this phase the step vector (S) is adjusted periodically to better follow the function behavior. The best point is recorded as Xopt.

Step4: Once thermal equilibrium is reached, the temperature (T) is reduced and a new sequence of moves is made starting from Xopt. Until thermal equilibrium is reached again.

Step5: This process is continued until a sufficiently low temperature is reduced, at which stage no more improvement in the objective function value can be expected.

3. ROSENBROCK SEARCH (RS):

RS [9] is based on the "Automatic" method proposed by H.H.Rosenbrock. This method is a sequential search technique and solves the problem.

$$\text{Optimize } F(x_0^{(k)}, x_1^{(k)} \text{ ---------- } x_n^{(k)}) \quad (3)$$

$$\text{Subject to } G_K < X_K < H_K \quad (4)$$

The implicit variables x_{N+1} ------x_M are dependent functions of the explicit independent variables $x_0^{(k)}$, $x_1^{(k)}$ ---------- $x_n^{(k)}$.The upper and lower constraints G_K and H_K are either constants or functions of the independent variables. The goal of RS is to search for the minimum of a nonlinear object function. It is an iterative procedure that bears some

correspondence to the exploratory search of Hooke and Jeeve's in that small steps are taken during the search in orthogonal coordinates. However, instead of continually searching the coordinates corresponding to the directions of the independent variables, an improvement can be made after one cycle of coordinate search by lining the search direction up into orthogonal systems, with the overall step on the previous stage as the first building block for the new search coordinates. In this method, the coordinate system is rotated in each stage of minimization in such manner that the first axis is oriented towards the locally estimated direction of valley and all other directions are made mutually orthogonal and normal to the first one. Each step is tested for success i.e. from $x_1^{(k)}$ if we take the step length $\lambda_1^{(k)}$ to search $x_2^{(k)}$ and if f $(x_2^{(k)}) < f(x_1^{(k)})$, then the step is treated as success. Otherwise it is a failure.

3.1 RS Algorithm:

Let the function to be minimized be a function of n variables. Selection of a set of initial step length $\lambda_1^{(k)}$, --------, $\lambda_n^{(k)}$ to be taken along the search directions $S_1^{(k)}, S_2^{(k)}$ ---- $Sn^{(k)}$ respectively forms the beginning of process. The procedure for k^{th} stage is given below.

Step1: The set of $S_1^{(k)}, S_2^{(k)}$ ---- $Sn^{(k)}$ and the base points $x_0^{(k)}$ are known at the beginning of k^{th} stage. A step length $\lambda_1^{(k)}$ in the direction $S_1^{(k)}$ from the known base point is considered. If step is successful, the step width is increased, $\lambda 1^{(k)}$ is multiplied by a factor α,the new point is retained and a success is recorded. If step is a failure, the step width is decreased, $\lambda_1^{(k)}$ is multiplied by a factor β and a failure is recorded. The values of α and β recommended by Rosenbrock are α=3 and β=-0.5.

Step2: The search is continued along the direction $S1^{(k)}, S_2^{(k)}$ ---- $Sn^{(k)}$ until at least one step has been successful and one step has failed in each of n directions.

Step 3: The new set of directions for use in Gram-Schmidt orthogonalisation process,

$S_1^{(k+1))}$, ------, $Sn^{(k+1)}$ are computed as under:

(a) Compute the An×n matrix according to the relation:

$$An\times n = [A_1^{(k)}, A_2^{(k)}, \text{---------} An^{(k)}] \quad (5)$$

$$A_1^{(k)} = \wedge_1^{(k)} S_1^{(k)} + \wedge_2^{(k)} S_2^{(k)} + \text{---------} + \wedge_n^{(k)} S_n^{(k)}$$

$$A_2^{(k)} = \quad + \wedge_2^{(k)} S_2^{(k)} + \text{--------} + \wedge_n^{(k)} S_n^{(k)}$$

$$\text{----------} \quad (6)$$

$$An^{(k))} = \quad \wedge_n^{(k)} S_n^{(k)}$$

Where $A_1^{(k)}$ is the vector from $x_0^{(k)}$ to $x_0^{(k+1)}$, $A_2^{(k)}$ is the vector from $x_1^{(k)}$ to $x_0^{(k+1)}$, and so on. $A_1^{(k)}$ represents the overall move from stage k to stage (k+1), $A_2^{(k)}$ represents the overall move less the progress made during the search in direction $s_1^{(k)}$,etc. and $\wedge_i^{(k)}$ be the algebraic sum of all the successful steps (the net distance moved) in the direction $S_i^{(k)}$during the k^{th} stage.

(b)Set $B_1^{(k)} = A_1^{(k)}$ and $s_1^{(k+1)} = A_1^{(k)} / \| A_1^{(k)} \|$ (7)

(c)Find $B_n^{(k)} = A_n^{(k)} - \Sigma [(A_n^{(k)})^T S_i^{(k+1)}] S_i^{(k+1)}$

With $Si^{(k+1))} = B_n^{(k)} / \| B_n^{(k)} \|$ (8)

Where $\| A_i^{(k)} \|$is the normal of $A_i^{(k)}$

Step4: Take the best obtained in the present stage as the best point for the next stage .Set the new iteration number as (k+1) and repeat the procedure.

Step5: Convergence is assumed after completing specified number of stages or after satisfying the condition $| \lambda_k^{(k)} | \leq \varepsilon$ for all n, where ε is a specified error limit.

4. HYBRID OPTIMIZATION ALGORITHM:

In this section, we developed a hybrid optimization algorithm based on the principles of both the aforementioned SA and RS. The SA method occasionally chooses those 'uphill points' from the current place. That is, not only the improved solutions but also the relatively weak ones are accepted with a specified probability according to different temperatures. Thus the SA method has certain advantages, e.g., robustness and flexibility, over other local search methods, and is suitable for handling nonlinear problems. Unfortunately, it always takes a considerably long time to acquire the global optimum, because the temperature indeed needs to be decreased slowly enough during the iterations. A main advantage of creating a hybrid [10-17] of global optimization with traditional methods is that the traditional methods have faster and closer convergence at the same time and the global techniques guarantee convergence to global minima.

The design space of mechanism contains a large number of local minima. A local optimization algorithm starting from random points will converge to the nearest local minimum which may be an unsatisfactory design. The hybrid SADS algorithm developed here is combination of SA and RS. In this algorithm, as the SA procedure progresses, a list of twenty best points is simultaneously maintained and constantly updated after a new point is randomly created. At the termination of SA algorithm, these points are fed to RS algorithm as the starting points for the local search and new list of best points is created.

5. PROBLEM FORMULATION:

This section address the problem of minimizing the error of function generating linkages under inequality constrains. Formulation of an optimal design problem involves identification of the design variables, **X,** objective function, f(**X**), and design constraints. Design optimization is the process of finding the optimal parameters which yield maximum or minimum f(**X**), which must also satisfy a certain set of specified requirements. Optimal synthesis procedure commonly minimizes the "structural error", the error at a point in domain and is defined as the difference between the actual output displacement and the required output displacement. The design of mechanism can be formulated as a problem in non linear programming (NLP).

5.1. Objective Function:

The f(**X**) for the synthesis of function generation problem has been formulated from the structural errors. Usually, in function generating mechanism design problem, a relation exists between the rotation angle of the input link, the expected angle of output link (Φ_{EXP}) and the generated angle of the output link ((Φ_{GEN}). The mean root value of error between (Φ_{EXP}) and (Φ_{GEN}) is generally used as f(**X**) to be minimize. The objective function [6, 20, 22], f(**X**), is taken as the sum of the squares of structural errors (in radians) at different precision points. The implicit and the explicit constraints are incorporated as the penalty functions in the SA and RS Algorithm. The f(**X**) of the problem for minimisation can be expressed mathematically as:

$$f(\mathbf{X}) = \Sigma \; [(\Phi_{EXP}) - (\Phi_{GEN})]^2 \qquad (9)$$

The output angle generated by the mechanism is considered as a function of input angle (Θ) in the following form:

$$(\Phi - \Phi s)k_2 = f[(\Theta - \Theta s)\, k_1] \qquad (10)$$

$$\text{Where } f(\Theta) = A_1 \Theta^3 + A_2 \Theta^2 + A_3 \Theta + A_4 \;] \qquad (11)$$

Thus the expected value of output angle is calculated from the extension of above equation as

$$\Phi_{EXP} = [f[(\Theta - \Theta s)\, k_1] / K_2 + \Phi s \qquad (12)$$

Table1 shows values of A_1, A_2 $A_3$and A_4 taken in the above equation.

Table 1: Values of function coefficients

A_1	A_2	A_3	A_4
2.5×10^{-6}	9×10^{-4}	0.12	20

Generated value of the output angle is a function of the link ratios X_1, X2 and X_3 and input angle (Θ). The objective function for minimization is taken in (rad^2) and in the form as given below –

$$f(\mathbf{X}) = \sum [f(\Theta - \Theta s)\, k_1 - (\Phi_{GEN} - \Phi s)\, K_2 \;]^2 \qquad (13)$$

The values of input angle (Θ) are taken in the range of 15 ^{o} to 180^o in steps of 15 ^{o} to produce twelve precision positions.

5.2. Design variables and Parameters:

In this optimization problem, design variable vector **X** =[X1, X_2, ------- X_7], represents a solution that minimize the objective function.Parameters used in the formulation of objective function are as follows:

1. Ratio of Coupler/ Crank length = X_1
2. Ratio of Rocker / Crank length = X_2
3. Ratio of Fixed link/ Crank length = X_3
4. Initial starting angle of Crank link = X_4
5. Initial starting angle of Rocker = X_5
6. Scale for (Θ) = X_6
7. Scale for (Φ) = X_7

5.3. Constraints:

Constraints are the conditions that must be met in the optimum design and include restrictions on the design variables. These constraints define the boundaries of the feasible and infeasible design space domain. The constraints considered for the optimum MSP are as follows:

1. $0.0 <, X_1, X_2, X3 \leq 4.0$
2. $0^o \leq X_4, X_5 \leq 15^o$
3. $0.0 \leq X_6, X_7 \leq 2.0$

6. RESULTS AND DISCUSSION:

The SA has been developed and later on hybridizing externally with RS, the local search provides the fastest solutions at the end of each generation. The newly developed Hybrid SADS has been tried on standard test problems for testing their effectiveness both as global optimization procedure and for faster and closer convergence. The Four bar function generator was optimally optimized using SA and also using hybrid SADS. On getting satisfactory results from SA, RS is activated and carries out local search to gain

accuracy. The results of this simulation are obtained by varying the seed values, number of iteration, and number of precision points. Many solutions were obtained globally and seed values for hybrid SADS are varied and applied number of times and 20 best solutions are selected for the presentation.

Table2 to Table5 depicts the details of objective function (rad²), maximum and minimum error in degrees. Table6 to Table7and Fig1 to Fig2 show the best solution obtained by SA and hybrid SADS respectively.

6.1. Results Obtained By Global Iteration (SA):

Table 2 Objective Function (Rad²), Maximum and Minimum error for 20 best solutions.

Best Points	Objective Function	Maximum error(deg)	Minimum error (deg)
1	0.00271	-2.4991	-0.03631
2	0.00281	-2.5849	-0.04861
3	0.00301	-2.5896	-0.04983
4	0.00326	-3.0931	-0.0529
5	0.00330	-2.6872	-0.0556
6	0.00365	-3.0856	-0.04876
7	0.00383	-35621	-0.0551
8	0.00384	-2.9865	-0.0589
9	0.00398	-3.1872	-0.0529
10	0.00399	-3.3567	-0.0623
11	0.00423	-3.8956	-0.0671
12	0.00426	-2.5590	-0.0583
13	0.00430	-3.5981	-0.0677
14	0.00440	-2.5849	-0.0689
15	0.00441	-3.1955	-0.0466
16	0.00464	-3.2283	-0.0489
17	0.00445	-3.5892	-0.0586
18	0.00450	-3.7429	-0.0487
19	0.00462	-3.3651	-0.0494
20	0.00463	-2.5956	-0.0631

Table 3 Structural error ($\Phi_{EXP} - \Phi_{GEN}$) in degrees for the best solution out of 20 best points

Θ	Φ_{EXP}	Φ_{GEN}	($\Phi_{EXP} - \Phi_{GEN}$)
15	20.3634	22.862636	-2.4991 maximum
30	21.0668	22.08039	-1.01352
45	21.8262	21.90171	-0.07543
60	22.6440	22.2485	0.3955
75	23.5224	22.9955	0.52695
90	24.4639	24.01686	0.44788
105	25.4708	25.20385	0.26696
120	26.5454	26.46704	0.07839
135	27.5454	27.72870	-0.03855
150	28.9073	28.94363	-0.03631 minimum
165	30.1993	30.048931	0.150369
180	30.6955	30.11340	0.5821

6.1. Results Obtained By Hybrid SADS:

Table 4 Objective Function (Rad²), Maximum and Minimum error for 20 best solutions.

Best Points	Objective Function	Maximum error(deg)	Minimum error (deg)
1	0.00111	-2.20099	-0.02372
2	0.00165	-2.8531	-0.02898
3	0.00152	-2.6148	-0.04347
4	0.00200	-2.5861	-0.04897
5	0.00310	-2.5542	-0.0386
6	0.00268	-2.6687	-0.0549
7	0.00208	-2.8549	-0.0366
8	0.00211	-2.6935	-0.0458
9	0.00298	-2.1872	-0.0389
10	0.00154	-2.287	-0.0583
11	0.00231	-2.6158	-0.0566
12	0.00242	-2.5590	-0.0486
13	0.00263	-2.5981	-0.0589
14	0.00226	-2.4797	-0.0574
15	0.00263	-2.4965	-0.0348
16	0.00137	-2.1956	-0.0378
17	0.00279	-2.3773	-0.0437
18	0.00220	-2.578	-0.0372
19	0.00121	-2.5572	-0.0385
20	0.00192	-2.4762	-0.0584

Table5 Structural error($\Phi_{EXP} - \Phi_{GEN}$) in degrees for the best solution out of 20 best points.

Θ	Φ_{EXP}	Φ_{GEN}	($\Phi_{EXP} - \Phi_{GEN}$)
15	20.0000	22.20101	-2.20099 maximum
30	20.6736	21.42994	-0.75626
45	21.4020	21.25657	0.14547
60	22.1874	21.60450	0.58295
75	23.0322	22.35025	0.682
90	23.9388	23.36922	0.56959
105	24.9094	24.55331	0.35616
120	25.9465	25.81329	0.13329
135	27.0525	27.07622	-0.02372

			minimum
150	**28.2295**	**28.28236**	**-0.05278**
165	**29.4801**	**29.38304**	**0.09714**
180	**30.8066**	**30.33934**	**0.46729**

7. CONCLUDING REMARKS:

The paper may be concluded with the following observations:

1. A hybrid optimization method based on the fusion of the SA and RS is developed and applied on MSP. A newly developed hybrid SADS is effective and fast in the solution of MSP.It also shows closer convergence properties.
2. A hybrid SADS can be applied for other MSP such as path generation and rigid guidance problem.
3. The results are encouraging and suggest that a hybrid SADS can be used effectively and efficiently in other complex and realistic design often encountered in engineering applications.
4. From Table 3 and Fig.1, the minimum error = **-0.03631**At$150^0$and the maximum error=**-2.4991** at 15^0 for SA whereas From Table 5 and Fig.2, the minimum error = **-0.02372**at$135^0$and the maximum error=**-2.20099**at $15^0$for hybrid SADS. Thus it can conclude from computer simulation results that a hybrid SADS is an effective tool for MSP.

8. SCOPE OF FUTURE WORK:

This work can be extended for the development of hybrid algorithm by using SA as a local search algorithm with in a tabu search, ant colony optimization etc.or by using SA as a global search algorithm with in other classical non linear programming technique that can improve solutions and accelerate convergence. It can be extended for MSP such as path generation and rigid body guidance problem.

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Table6 Parameters in the objective function obtained by Global iteration (SA)

Best Points	X1	X2	X3	X4	X5	X6	X7
1	3. 9883	3.3509	3.5582	6.7595	4.5894	0.3595	0.2654
2	2. 9638	2.1036	3.4839	13.8856	13.9589	0.4176	0.2551
3	2 .9326	2.3226	3.2414	3.5924	4.2375	0.4228	0.2568
4	3.437	2.9677	3.3001	4.868	11..4956	0.3526	0.2774
5	3.3787	3.0929	2.8309	13.9003	9.6334	0.368	0.2757
6	2.9365	2.8074	3.0186	6.173	14.0616	0.3629	0.262
7	2.7058	1.6891	3.0694	6.2903	1.349	0.4912	0.2551
8	3.3275	1.9824	3.9648	3.5191	11.2463	0.522	0.2774
9	2.5806	2.2053	2.5885	12.8886	13.6657	0.4809	0.2945
10	3.4213	2.2991	3.7224	0.088	4.2669	0.469	0.2739
11	3.566	3.0694	3.304	11.7449	14.2375	0.2945	0.2705
12	3.1007	2.0137	3.8123	13.2551	10.3519	0.5357	0.2568
13	3.1711	2.8583	2.870	12.6393	11.2903	0.4228	0.2842
14	3.781	3.2414	3.3353	1.393	11.4663	0.4074	0.3013
15	2.5689	1.8964	3.0499	14.7947	11.0264	0.5459	0.2671
16	3.9883	2.9599	3.8788	5.1613	10.8358	0.2893	0.2568
17	3.4565	3.2297	2.7957	8.2845	5.2493	0.3697	0.2757
18	3.6442	3.2023	3.2649	6.129	9.8387	0.2962	0.2688
19	3.824	2.5885	3.8553	0.4106	3.5484	0.4142	0.262
20	3.347	1.8573	3.781	5.3372	11.2463	0.4707	0.2688

Table7 Parameters in the objective function obtained by Hybrid SADS

Best Points	X1	X2	X3	X4	X5	X6	X7
1	3. 9993	3.3509	3.5582	14.9995	7.2944	0.3595	0.2654
2	2. 9848	2.1816	3.4899	14.9996	3.9609	0.4496	0.2611
3	2 .2876	2.4046	3.2414	14.9994	4.3895	0.4228	0.2668
4	3.5810	2.9677	3.3041	14.9990	11..5356	0.3756	0.2784
5	3.3933	3.0929	2.8329	14.9993	9.6334	0.368	0.2777
6	3.0965	2.8074	3.0186	14.9990	14.0876	0.3689	0.2710
7	2.7328	1.8311	3.0694	14.9990	4.3760	0.5192	0.2611
8	3.5425	2.0074	3.9648	14.9991	14.9993	0.5270	0.2894
9	2.6006	2.2093	2.5915	14.9996	13.6657	0.4829	02995
10	3.6143	2.3161	3.7294	15.0000	11.0039	0.469	0.2879
11	3.5830	3.1244	3.3070	14.9999	14.2455	0.3545	0.2775
12	3.4867	2.0137	3.8223	14.9991	11.7019	0.5357	0.2888
13	3.3961	2.8583	2.8820	14.9993	11.3973	0.4228	0.3032
14	3.9990	3.2414	3.3464	14.9990	14.9993	0.4074	0.3173

15	2.7309	1.8964	3.0499	14.9997	11.1784	0.5459	0.2861
16	3.9993	3.0409	3.8868	14.9993	11.9938	0.3653	0.2728
17	3.7075	3.2297	2.7977	14.9995	5.3443	0.3847	0.2867
18	3.7162	3.2203	3.2699	14.9990	9.8637	0.3452	0.2698
19	3.9310	2.6345	3.8733	14.9996	7.7004	0.4142	0.2750
20	3.3490	2.0363	3.7890	14.9992	14.7773	0.5107	0.2828

Fig1 : Best Solution Obtained By Global iteration (SA)

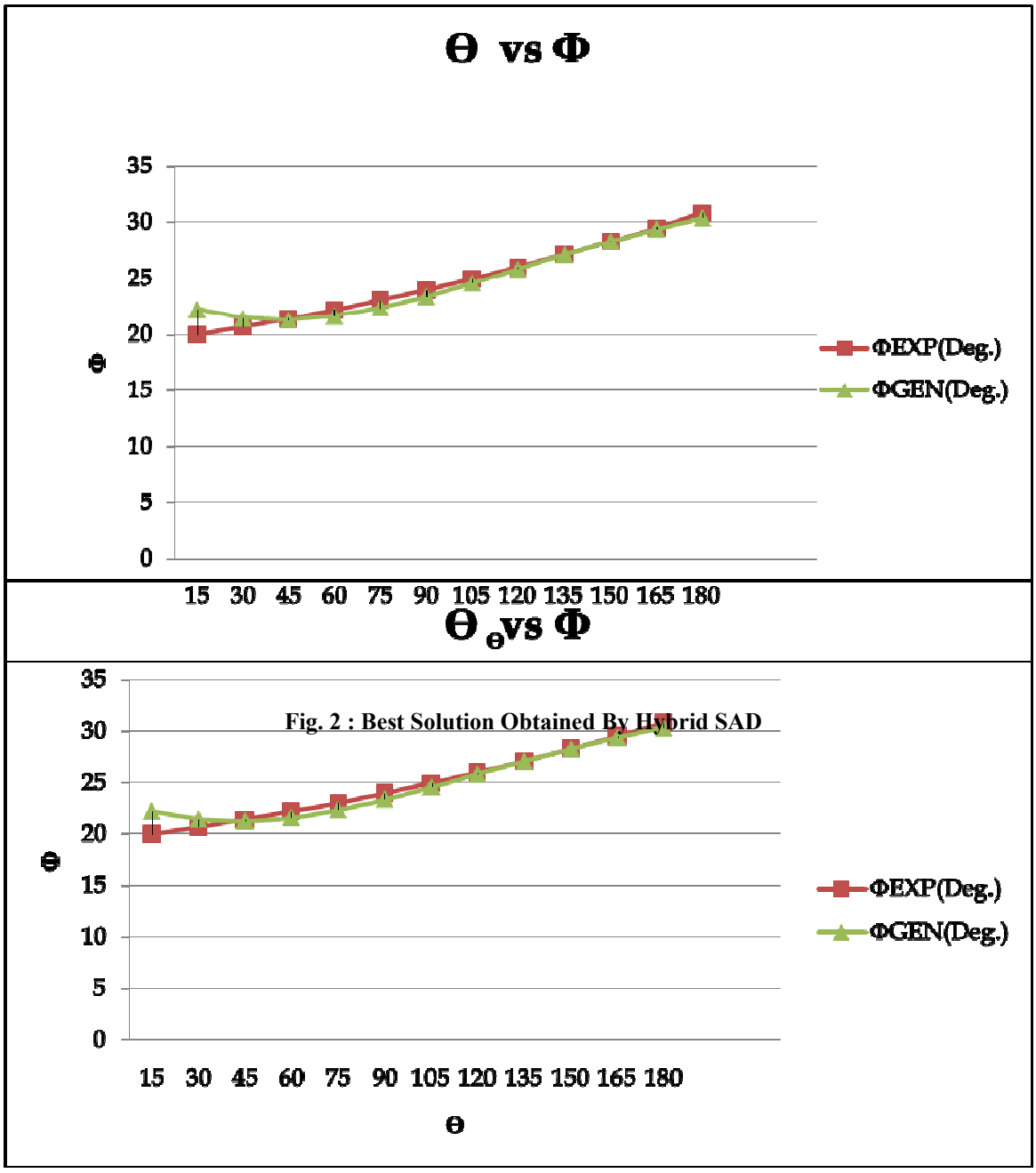

Fig. 2 : Best Solution Obtained By Hybrid SAD