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A Coupled Simulated Annealing-Hill Approach for Mechanism Synthesis with Twenty Accuracy Points

[#1]Dr. M.K. Sonpimple, [#2]M. S. Matey

[1]msonpimple@gmail.com
[2]msmateyonline@gmail.com

[#1]Professor, Department of Mechanical Engineering, Priyadarshini Collegeof Engineering, RastrasantTukdojiMaharaj Nagpur University, Nagpur, Maharashtra, India.

[#2]Assistant Professor, Department of Mechanical Engineering,Priyadarshini Collegeof Engineering, RastrasantTukdojiMaharaj Nagpur University, Nagpur, Maharashtra, India.

ABSTRACT

This paper proposes a novel approach for the Optimization of mechanism synthesis for function generation problem with twenty accuracy points using a hybrid search algorithm. A hybrid optimization method is based on the fusion of the Simulated annealing (SA) and Rosenbrock Search (RS), derivative-free type method of optimization, called SA/ RS, in which the SA is embedded the RS to enhance its search capability. The algorithm combines the advantages of the global optimization technique and a classical non linear programming technique. An overview of SA/ RS 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 SA/ RS 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 experimental results manifest that the proposed hybrid approaches are effective and efficient in finding near optimal solutions.

Keywords: Function generation, Hybrid algorithm, Rosenbrock Search, Simulated annealing.

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I. 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 these 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 error 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 thedesigner to reduce this error to a sufficiently low value. Many numerical optimizations [8-10] 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

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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.

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 unpreferrable. For this reason, many SA implementations have been done as a part of a hybrid method [11-22].

In this paper, 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 Four bar function generator was optimally optimized using SA and also using SA/ RS. On getting satisfactory results from SA, RS is activated and carried out local search to gain accuracy i.e. when SA procedure is in progress; a list of twenty best points is maintained and constantly updated, iff 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.

II. SIMULATED ANNEALING

A. Fundamental Concept:

SA [8-9] 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, (ri), exhibiting a specific energy, E (ri), at some temperature T, is defined by the Boltzmann Probability factor:

$$P (E (ri)) = e – [E (ri) / kBT] \quad (1)$$

Where kB 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 kB, 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:

$$P[accept\ Xt]= e – [f (xt) – f (xo) / CT] \quad (2)$$

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

B. SA Algorithm

The algorithm proceeds as follows:

Step1: Starting from the initial point X0, the algorithm generates successively improved points X1, X2…… moving towards the global minimum solutions. The initial value of a control parameter (T) is suitably high and a methodology for decrementing (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.

III. ROSENBROCK SEARCH

A. Fundamental Concept:

RS [8-10] is based on the "Automatic" method proposed by H.H.Rosenbrock. This method is a sequential search technique and solves the problem.

Optimize F(x0(k), x1(k) ---------- xn (k)) (3)

Subject to GK < XK< HK (4)

The implicit variables xN+1 ------xM are dependent functions of the explicit independent variables x0(k), x1(k) ---------- xn (k).The upper and lower constraints GK and HK 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 x1(k) if we take the step length λ1 (k) to search x2(k) and if f (x2(k)) < f (x1(k), then the step is treated as success. Otherwise it is a failure.

B. RS Algorithm:

Let the function to be minimized be a function of n variables. Selection of a set of initial step length λ1 (k), --------, λn (k) to be taken along the search directions S1 (k,) , S2 (k) ----

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Sn (k) respectively forms the beginning of process. The procedure for kth stage is given below.

Step1: The set of S1 (k,) S2 (k) ---- Sn (k) and the base points x0(k) are known at the beginning of kth stage. A step length $\lambda 1$ (k) in the direction S1 (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 $\alpha=3$ and $\beta=-0.5$.

Step2: The search is continued along the direction S1 (k,) S2 (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,
S1 (k+1)), ------, Sn (k+1) are computed as under:
Compute the An×n matrix according to the relation:

An×n=[A1 (k), A2(k),---------An(k)] (5)

A1 (k) = $\wedge$1(k) S1 (k) + $\wedge$2(k) S2 (k) +--------+$\wedge$n (k) Sn (k)
A2 (k) = + $\wedge$2(k) S2 (k) +--------+$\wedge$n (k) Sn (k) (6)
An (k)) = $\wedge$ n (k) Sn (k)

Where A1 (k) is the vector from x0(k) to x0(k+1), A2 (k) is the vector from x1(k) to x0(k+1), and so on. A1(k) represents the overall move from stage k to stage (k+1), A2(k) represents the overall move less the progress made during the search in direction s1(k),etc. and $\wedge$i(k) be the algebraic sum of all the successful steps (the net distance moved) in the direction Si (k)during the kth stage.

(b)SetB1(k)=A1(k)ands1(k+1)=A1(k)⁄||A1(k)||(7)

(c)Find Bn (k) = An (k) −Σ [(An (k)) T Si (k+1)] Si (k+1) With Si (k+1)) = Bn (k) ⁄||Bn (k) || (8)

Where || Ai (k) ||is the normal of Ai. (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 | λk (k) | ≤ ε for all n, where ε is a specified error limit.

IV. HYBRID OPTIMIZATION ALGORITHM

Any one algorithm may not be sufficient to provide a satisfactory solution for the given problem at hand.In recent years there has been a great deal of interest in the development of optimization algorithms that deal with the problem of finding a global minimum of a given continuous function. These algorithms were innovated to confront the rapid growth of many optimization problems in engineering.
Meta-heuristics methods are considered to be acceptably good solvers of this problem. The power of meta-heuristic methods come from the fact they are robust and can deal successfully with a wide range of problem areas.
However, these methods, especially when they are applied to complex problems, suffer from the high computational cost due to their slow convergence. The main reason for this slow convergence is that these methods explore the global search space by creating random movements without using much local information about promising search direction. In contrast, local search methods have faster convergence due to their using local information to determine the most promising search direction by creating logical movements. The local search methods can easily be entrapped in local minima. One approach that recently has drawn much attention is to combine meta-heuristic methods with local search methods to design more efficient methods with relatively faster convergence than the pure meta-heuristic methods. Moreover, these hybrid methods are not easily entrapped in local minima because they still maintain the merits of the meta-heuristic methods.

The reason for studying and developing a hybrid algorithm can be summarized as follows:

1. To improve the performance of the Non-traditional search computation (NTSC).
(Example: fast convergence speed and robustness) i.e. SA method usually suffers from slow convergence due its random nature of movements. Moreover, it also suffers from the difficulty in obtaining some required accuracy although it may quickly approach the neighborhood of the global minimum. Hence we have focused on the importance of creating the hybrid approach and importance of accelerating the final stage of SA by using the faster convergent method.

2. To improve the quality of the solutions obtained by the NTSC.

3. It achieves the searching not only globally but also locally.

4. To prevent the premature convergence.
In order to prevent the premature convergence, the coupling of SA and local search methods, to form hybrid SA/RS can be advantageous.

5. It searches larger regions of the solution space effectively using both SA-based global search capability with traditional search-based local search feature.

6. The goal of developing a Hybrid simulated Annealing approach is to use this algorithm to help in solving the problem of optimal synthesis of a mechanism for the function generation problem.
Achieving this goal will help in providing the best set of design variables, reducing the structural error and satisfying number of design constraints.

7. Modern meta-heuristics manage to combine exploration and exploitation search.
The exploration search seeks for new regions, and once it finds a good region, the exploitation search kicks in. However, since the two strategies are usually inter-wound, the search may be conducted to other regions before it reaches the local optima. As a result, many researchers suggest employing a hybrid strategy, which embeds a local optimizer in between the iterations of the meta-heuristics.
The diagram of scheme SA/ RS is shown in Fig.1

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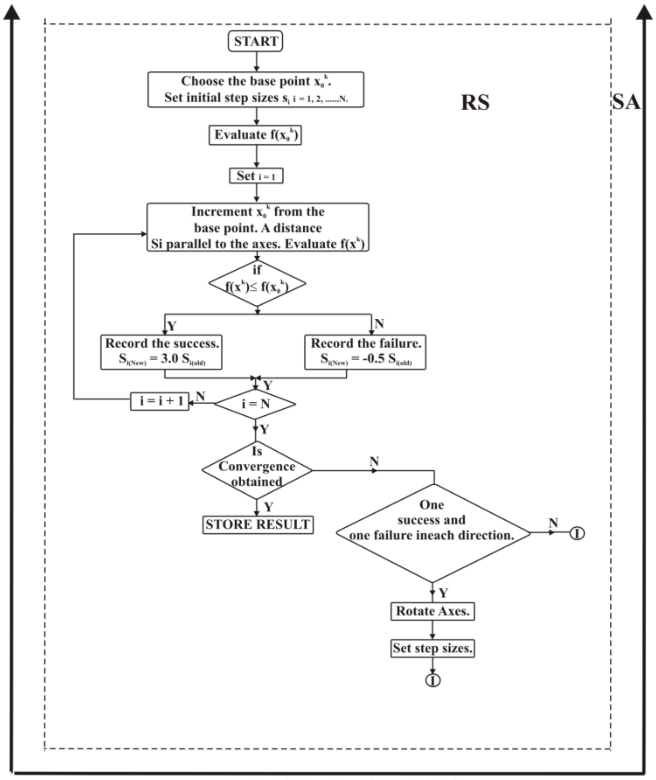

Fig. 5.2 Flow chart of Hybrid SADS

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 [18-22] of global optimization with traditional methods is to improve the global search and convergence speeds.

V. 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. 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).

A. Objective Function:

Usually, in function generating mechanism design problem, a relation exists between the rotation angle of the input link, the expected angle of output link(ΦEXP) and the generated angle of the output link ((ΦGEN). The mean root value of error between (ΦEXP) and (ΦGEN) is generally used as f(X) to be minimize. The objective function, 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:

$$f(\mathbf{X}) = \sum_{\Theta=180^o/N}^{180^0} [(\Phi_{EXP}) - (\Phi_{GEN})]^2 \quad (9)$$

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

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

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

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

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

Table I shows values of A_1, A_2 $A_3$and A_4 used in above equations.

Table I
Values of function coefficients

Function Type	A_1	A_2	A_3	A_4
FunType1	3×10^{-6}	5×10^{-4}	0.385	65

Generated value of the output angle is a function of the link ratios X_1,X_2 and X_3 and input angle(Θ).The objective function for minimization is taken in (rad^2)and in the form as given below :–

$$f(X) = \sum_{\Theta=180^o/N}^{180^0} [f\,(\Theta - \Theta s)\,k_1 - (\Phi_{GEN} - \Phi s)\,K_2 \;]^2 \quad (13)$$

The values of input angle (Θ) are taken in the range of 180^o / N to 180^o in steps of 180^o / N to produce N precision positions.

B. *Design variables*:

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

C. *Constraints***:** The constraints considered for the optimum MSP are as follows:

1. 0.0<, X_1, X_2 ,$X_3 \leq 4.0$
2. $0^o \leq X_4$,$X_5 \leq 15^o$
3. $0.0 \leq X_6$, $X_7 \leq$ 2.0

VI. RESULTS AND DISCUSSION

A newly developed SA/RS has been tried on standard test problems for testing their effectiveness both on global optimization procedure conversely for faster and closer convergence. 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 locally. The number of best solutions, number of iteration,

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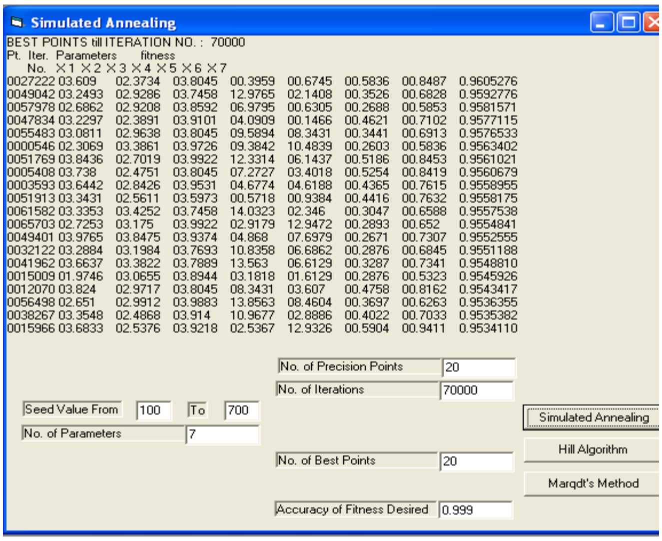
and number of precision points selected for the presentation are as follows:
(i)Number of best solutions=20 (ii) Number of iteration=70000 (iii) Number of precision points=20
Table II to Table VI depicts the details of Best 20 solution, Objective Function (Rad²), Structural error in degrees for the best 20 points. Fig.1to Fig.2 shows the best solution obtained by SA and SA/RS.

A. *Results obtained by global Iteration (SA) for 20 accuracy points:*

TABLE II

20 BEST POINTS FOR 20 ACCURACY POINTS –SA


Simulated Annealing
BEST POINTS till ITERATION NO. : 70000

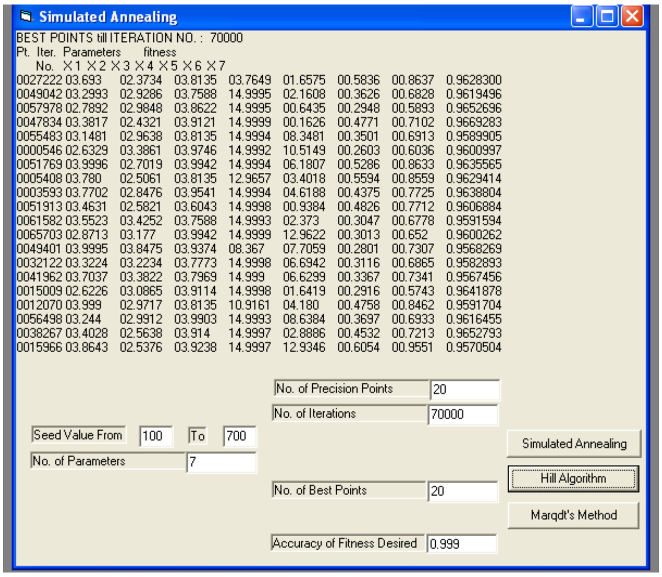
Pt. Iter. No.	X1	X2	X3	X4	X5	X6	X7	fitness
0027222	03.609	02.3734	03.8045	00.3959	00.6745	00.5836	00.8487	0.9605276
0049042	03.2493	02.9286	03.7458	12.9765	02.1408	00.3526	00.6828	0.9592776
0057978	02.6862	02.9208	03.8592	06.9795	00.6305	00.2688	00.5853	0.9581571
0047834	03.2297	02.3891	03.9101	04.0909	00.1466	00.4621	00.7102	0.9577115
0055483	03.0811	02.9638	03.8045	09.5894	08.3431	00.3441	00.6913	0.9576533
0000546	02.3069	03.3861	03.9726	09.3842	10.4839	00.2603	00.5836	0.9563402
0051769	03.8436	02.7019	03.9922	12.3314	06.1437	00.5186	00.8453	0.9561021
0005408	03.738	02.4751	03.8045	07.2727	03.4018	00.5254	00.8419	0.9560679
0003593	03.6442	02.8426	03.9531	04.6774	04.6188	00.4365	00.7615	0.9558955
0051913	03.3431	02.5611	03.5973	00.5718	00.9384	00.4416	00.7632	0.9558175
0061582	03.3353	03.4252	03.7458	14.0323	02.346	00.3047	00.6588	0.9557538
0065703	02.7253	03.175	03.9922	02.9179	12.9472	00.2893	00.652	0.9554841
0049401	03.9765	03.8475	03.9374	04.868	07.6979	00.2671	00.7307	0.9552555
0032122	03.2884	03.1984	03.7693	10.8358	06.6862	00.2876	00.6845	0.9551188
0041962	03.6637	03.3822	03.7889	13.563	06.6129	00.3287	00.7341	0.9548810
0015009	01.9746	03.0655	03.8944	03.1818	01.6129	00.2876	00.5323	0.9545926
0012070	03.824	02.9717	03.8045	08.3431	03.607	00.4758	00.8162	0.9543417
0056498	02.651	02.9912	03.9883	13.8563	08.4604	00.3697	00.6263	0.9536355
0038267	03.3548	02.4868	03.914	10.9677	02.8886	00.4022	00.7033	0.9535382
0015966	03.6833	02.5376	03.9218	02.5367	12.9326	00.5904	00.9411	0.9534110

The best desired accuracy of fitness for 20 accuracy points obtained by SA is **0.9605276**(first element of last column).
The best design vector is
X = **[**3.609, 02.3734, 03.8045, 0.3959, 0.6754, 0.5836, 0.8487**]** (first row).

B. *Results obtained by hybrid Iteration for 20 accuracy points (SA/RS):*

TABLE III

20 BEST POINTS FOR 20 ACCURACY POINTS SA/RS


Simulated Annealing
BEST POINTS till ITERATION NO. : 70000

Pt. Iter. No.	X1	X2	X3	X4	X5	X6	X7	fitness
0027222	03.693	02.3734	03.8135	03.7649	01.6575	00.5836	00.8637	0.9628300
0049042	03.2993	02.9286	03.7588	14.9995	02.1608	00.3626	00.6828	0.9619496
0057978	02.7892	02.9848	03.8622	14.9995	00.6435	00.2948	00.5893	0.9652696
0047834	03.3817	02.4321	03.9121	14.9999	00.1626	00.4771	00.7102	0.9669283
0055483	03.1481	02.9638	03.8135	14.9994	08.3481	00.3501	00.6913	0.9589905
0000546	02.6329	03.3861	03.9746	14.9992	10.5149	00.2603	00.6036	0.9600997
0051769	03.9996	02.7019	03.9942	14.9994	06.1807	00.5286	00.8633	0.9635565
0005408	03.780	02.5061	03.8135	12.9657	03.4018	00.5594	00.8559	0.9629414
0003593	03.7702	02.8476	03.9541	14.9994	04.6188	00.4375	00.7725	0.9638804
0051913	03.4631	02.5821	03.6043	14.9998	00.9384	00.4826	00.7712	0.9606884
0061582	03.5523	03.4252	03.7588	14.9993	02.373	00.3047	00.6778	0.9591594
0065703	02.8713	03.177	03.9942	14.9999	12.9622	00.3013	00.652	0.9600262
0049401	03.9995	03.8475	03.9374	08.367	07.7059	00.2801	00.7307	0.9568269
0032122	03.3224	03.2234	03.7773	14.9998	06.6942	00.3116	00.6865	0.9582893
0041962	03.7037	03.3822	03.7969	14.999	06.6299	00.3367	00.7341	0.9567456
0015009	02.6226	03.0865	03.9114	14.9998	01.6419	00.2916	00.5743	0.9641878
0012070	03.999	02.9717	03.8135	10.9161	04.180	00.4758	00.8462	0.9591704
0056498	03.244	02.9912	03.9903	14.9993	08.6384	00.3697	00.6933	0.9616455
0038267	03.4028	02.5638	03.914	14.9997	02.8886	00.4532	00.7213	0.9652793
0015966	03.8643	02.5376	03.9238	14.9997	12.9346	00.6054	00.9551	0.9570504

The best desired accuracy of fitness for 20 accuracy points obtained by SA/RS is **0.9669283**(fourth element of last column).
The best design vector is
X = **[**3.3817, 02.4321, 03.9121, 14.9999, 0.1626, 0.4771, 0.7102**]** (fourth row).

TABLE IV

OBJECTIVE FUNCTION (RAD^2) FOR 20 ACCURACY POINTS

Best Pts.	SA	SA/RS
1	**0.041094498**	0.038604946
2	0.042451111	0.039555503
3	0.043670187	0.03598
4	0.044155782	**0.034202846**
5	0.044219239	0.042763197
6	0.045653001	0.041558496
7	0.045913402	0.037821861
8	0.045950816	0.038484793
9	0.046139458	0.037473114
10	0.046224828	0.04092024
11	0.046294558	0.042579575
12	0.046589891	0.041638239
13	0.046840348	0.045121119
14	0.046990175	0.043526209
15	0.047250914	0.045209928
16	0.047567308	0.037142349
17	0.047842717	0.042567619
18	0.048618681	0.03988424
19	0.048725683	0.035969589
20	0.048865599	0.044877051

C. *Mechanism Synthesis Solution for 20 Accuracy Points*

TABLE V

STRUCTURAL ERROR WITH20 ACCURACY POINTS (SA)

θ	ϕ_{EXP}	ϕ_{GEN}	(ϕ_{EXP}) - (ϕ_{GEN})
9	66.9462	72.1724	-5.2262(max.)
18	69.0114	73.5856	-4.5742
27	71.1093	73.8261	-2.7168
36	73.2425	72.8729	0.3696(min.)
45	75.4136	73.6560	1.7576
54	77.6252	75.0783	2.5469
63	79.8800	77.0332	2.8468
72	82.1804	79.4156	2.7648
81	84.5292	82.1274	2.4018
90	87.9290	85.0795	2.8495
99	89.3823	88.1911	1.1912
108	92.8918	91.3886	1.5032
117	94.4601	95.3537	-0.8936
126	97.0897	98.7727	-1.683
135	99.7833	100.8351	-1.0518
144	102.5435	103.7337	-1.1902
153	105.3729	106.4150	-1.0421
162	108.2742	109.8307	-1.5565
171	112.2498	110.939	1.3108
180	114.3025	112.7077	1.5948

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TABLE VI

STRUCTURAL ERROR WITH20 ACCURACY POINTS (SA/RS)

θ	ϕ_{EXP}	ϕ_{GEN}	(ϕ_{EXP}) - (ϕ_{GEN})
9	63.9019	68.4253	-4.5234(max.)
18	65.5521	68.0488	-2.4968
27	67.2211	68.2903	-1.0692
36	68.9105	68.1540	0.7565
45	69.6217	68.6048	1.0169
54	71.3561	69.5826	1.7735
63	72.1150	71.0139	1.1011
72	73.9000	72.8218	1.0782
81	75.7125	74.9308	0.7817
90	77.5539	77.2696	0.2843
99	80.4255	79.7714	0.6541
108	83.3290	82.3739	0.9551
117	85.2655	85.0175	0.248(min.)
126	87.2367	87.6453	-0.4086
135	89.2439	90.2016	-0.9577
144	91.2885	92.6317	-1.3432
153	93.3720	93.8842	-0.5122
162	95.4957	96.9108	-1.4151
171	97.6615	98.6699	-1.0084
180	99.8698	100.1291	-0.2593

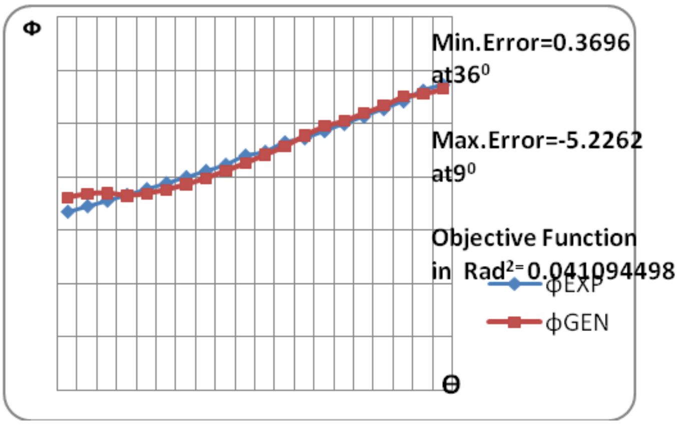

Fig.2 Best solution obtained by SA for 20 Accuracy Points

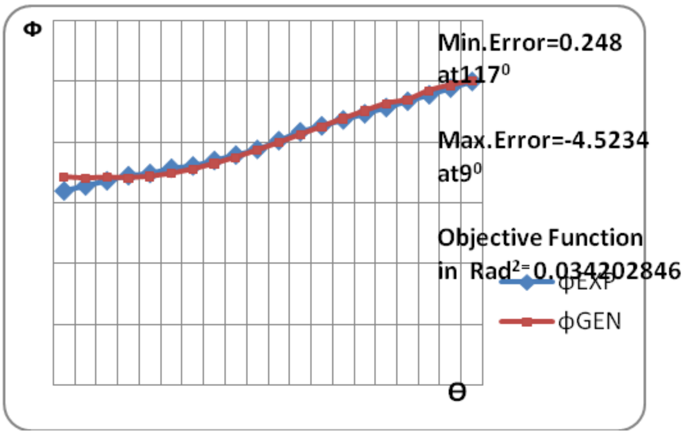

Fig. 3 Best solution obtained by SA/RS for 20 Accuracy Points

Simulation results Figs. (2-3) demonstrate the remarkable advantages of our approach in achieving the diverse optimal solutions and improved converge speed. It is clear that the hybrid approaches are effective and produce the good results for 20 accuracy points.

VII. 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 SA/RS is effective and fast in the solution of MSP. It also shows closer convergence properties.

2. The results are encouraging and suggest that SA/RS can be used effectively and efficiently in other complex and realistic design often encountered in engineering applications.

3. It can conclude from computer simulation results (Fig.2 and Fig3) that Minimum and Maximum error is greatly reduced by Hybrid iteration. Therefore SA/RS is an effective tool for MSP. The entire work may be concluded with the following observations.

4. Simulation results demonstrate the remarkable advantages of our approach in achieving the diverse optimal solutions and improved converge speed.

5. Hybrid algorithms have shown outstanding reliability and efficiency in application to the mechanism optimization problem.

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