# Multi-Objective Differential Evolution (MODE) Algorithm for Multi-Objective Optimization: Parametric Study on Benchmark Test Problems

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**Abstract:** Multi-Objective Differential Evolution (MODE), a multi-population, multi-objective optimization approach using Differential Evolution (DE) has been successfully applied to selected real world problems. This algorithm is equipped with non-dominated population selection combined with basic DE algorithm. In this study, the MODE algorithm is further applied on six different Test problems with/without constraints and extensive simulation runs are carried out for parametric study. Pareto optimal solutions are obtained for each test problems. The Pareto fronts are compared on the basis of various values of key MODE parameters. This work resulted in identifying the sensitivity of various key parameters of the MODE algorithm applied on the hard test problems.

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***Key Words:*** *Multi-objective optimization, Multi-Objective Differential Evolution (MODE), Pareto optimal front, Evolutionary computation, Population based search algorithms.*

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## 1. INTRODUCTION

Most realistic optimization problems, particularly those in engineering design, require the simultaneous optimization of more than one objective function. Some examples are listed in Table-1:

**Table-1: Applications of Multi-objective optimization in Engineering Design.**

| **Application** | **Objectives** |
|---|---|
| Complex test problems [8, 9] | Simultaneous maximization and minimization of several objectives in complex test problems |
| Chemical Plant Design [33] | Low total investment and high yield of product. |
| Aircraft Design [33] | High Fuel Efficiency, low payload, and low weight. |
| Car Purchase [33] | Low cost and high comfort |
| A good sunroof design in a car [33] | Low noise and high ventilation. |
| Automobile Design [33] | High crash resistance for safety and low weight for fuel economy. |
| Bridge Construction [33] | Low total mass and high stiffness. |
| Supply Chain Management [8], [37] | Minimum Manufacturing Cost, Total Operating Cost, Transportation cost and Maximum Revenue/Profit. |
| Wiped-Film Poly-Ethylene Terephthalate (PET) Reactor [22] | Minimization of acid end group concentration and vinyl end group concentration |
| Adiabatic Styrene reactor [23] | Maximization of productivity and yield |

In the applications listed in Table 1 and in many other cases, different solutions may produce trade-offs (conflicting scenario) among different objectives. A solution that is extreme with respect to one objective requires a compromise in other objectives. Hence, some trade-off between the criteria is needed to ensure a satisfactory design.

Because of a lack of suitable solution methodologies, a Multi-objective optimization problem (MOOP) has been mostly formulated and solved as a single objective optimization problem in the past by keeping one of the objectives as main objective and making other objectives as constraints. Traditionally, there are several methods available in the literature for solving MOOP problems [31]. These methods follow preference-based approach, where a relative preference vector is used to scalarize multiple objectives. Since classical search and optimization methods use a point-by-point approach, where

One solution in each of the iterations is modified to a different solution; the outcome of using classical method is a single optimized solution. However, Evolutionary Algorithms (EAs) can find multiple optimal solutions in a single simulation run due to their population based search approach.

In this paper, MODE, a simple and fast EA is applied on six different Test problems. As Differential Evolution is found to give better results than Genetic Algorithms (GA) for single objective optimization [18, 19, 20, 11, 24, 13], we tried to extend the application of DE to MOOP problems. In our previous work [22, 23], it was observed that results obtained by MODE and NSGA were exactly matching in terms of optimum objective function values. Though both NSGA and MODE follow the same Pareto optimal front, MODE is found to perform better in terms of convergence and diversity of the Pareto Optimal front with chosen parameter values. In this work, an attempt has been made to explore the performance and robustness of MODE algorithm by further applying it on six well known Test problems with various possible parameter values.

## 2. DIFFERENTIAL EVOLUTION

Differential Evolution [37] is an improved version of GA [32] for faster optimization. Unlike simple GA, that uses binary coding for representing problem parameters, DE is a simple yet powerful population based, direct search algorithm for globally optimizing functions with real valued parameters. Among the DE's advantages are its simple structure, ease of use, speed and robustness. Price and Storn [37] gave the working principle of DE with single strategy. Later on, they suggested ten different strategies of DE [39]. A strategy that works out to be the best for a given problem may not work well when applied for a different problem. Also, the strategy and key parameters to be adopted for a problem are to be determined by trial and error. Pseudo code of DE for solving single objective optimization is discussed in [22]. The crucial idea behind DE is a scheme for generating trial parameter vectors. Basically, DE adds a weighted difference between two population vectors to a third vector. The key parameters of control in DE are: *NP*, *CR*, and the *F*- the weight applied to random differential. Price and Storn [39] have given simple rules for choosing key parameters of DE for any given application. Babu et al. [24] proposed a new concept called 'nested DE' to automate the choice of DE key parameters. In addition, some new strategies have been proposed and successfully applied to the optimization of extraction process [14].

DE has been successfully applied in various fields. Some of the successful applications of DE include: digital filter design [40], batch fermentation process [41, 18], estimation of heat transfer parameters in trickle bed reactor [10], dynamic Optimization of a Continuous Polymer Reactor using a Modified Differential Evolution [34], optimization of Low Pressure Chemical Vapor Deposition Reactors Using Hybrid Differential

Evolution [35], optimal design of heat exchangers [19, 20], synthesis and optimization of heat integrated distillation system [17], optimization of an alkylation reaction [7], optimization of non-linear functions [12], optimization of thermal cracker operation [11], global optimization of MINLP problems [13], optimization of water pumping systems [15], optimization of biomass pyrolysis [6], etc. Many engineering applications using various evolutionary algorithms have been reported in the literature [1, 2, 3, 4, 5, 8, 9, 16, 21, 29, 36] etc.

## 3. MULTI-OBJECTIVE DIFFERENTIAL EVOLUTION (MODE)

Multi-Objective Differential Evolution (MODE) is a multi-population, multi-objective DE approach. The algorithm can be summarized as follows: An initial population is generated at random. All dominated solutions are removed from the population using the non-dominated sorting approach [31]. The remaining non-dominated solutions are retained for recombination. Three parents are selected at random. A child is generated from the three parents and is placed into the population if it dominated the first selected parent; otherwise a new selection process takes place. The schematic representation of MODE algorithm using DE approach is presented in Fig. 1. The general pseudo-code for MODE is reported in our earlier work [22, 23].

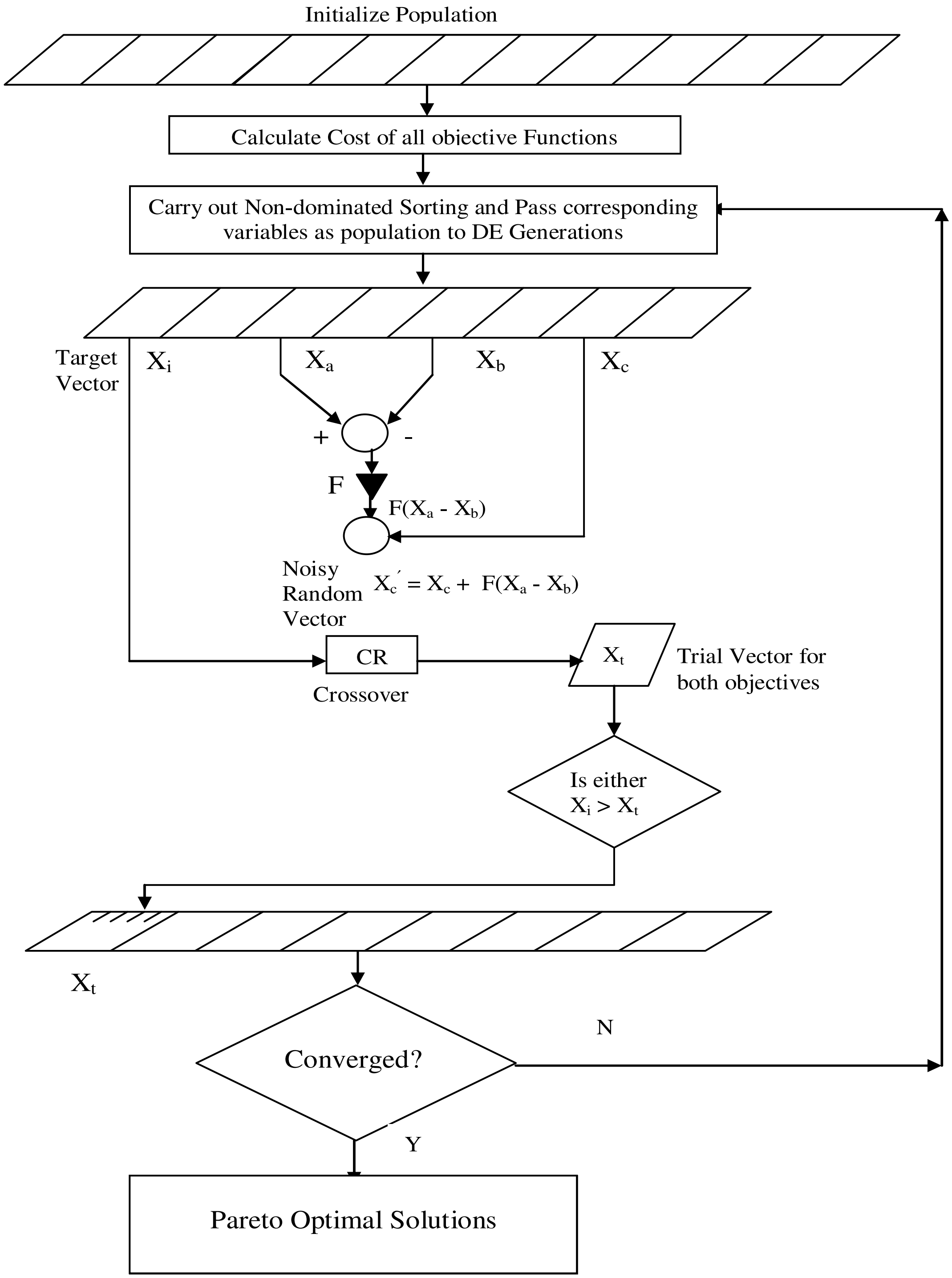


**Fig. 1 –working principle of MODE algorithm**

## 4. TEST PROBLEMS

Six well-known MO benchmark problems were used as a first step in the investigation of MODE's performance. Each Test problem consists of two objective functions with/without constraints. Test problems with constraints are handled by penalty approach. Since penalty terms are added to each objective function, the resulting penalized objective functions may form a Pareto optimal front different from the true Pareto optimal front, particularly if the chosen penalty parameter values are not adequate. For this purpose, the pseudo Pareto optimal front is determined by calculating the penalized function values using equations 1 and 2.

$$F_1 = f_1 + R_1\langle g_1\rangle + R_2\langle g_2\rangle \tag{1}$$

$$F_2 = f_2 + R_1\langle g_1\rangle + R_2\langle g_2\rangle \tag{2}$$

where $g_1$ and $g_2$ are constraints and R1 and R2 are the Penalty parameters of the respective objective functions. We considered the following Test problems for study [25, 26, 27, 31].

### *4.1. Test Problem - 1* [31]

$$\begin{aligned}
&\textit{Minimize} \quad f_1(d,l) = \rho\frac{\pi d^2}{4}l, \\
&\textit{Minimize} \quad f_2(d,l) = \delta = \frac{64Pl^3}{3E\pi d^4}, \\
&\textit{Subject to } \sigma_{\max} \le S_y, \\
&\qquad\qquad \delta \le \delta_{\max}, \\
&10 \le d \le 50\ mm \\
&200 \le l \le 1000\ mm.
\end{aligned}$$

where the maximum stress is calculated as follows:

$$\sigma_{\max} = \frac{32Pl}{\pi d^3}.$$

The following parameter values are used:

$$\sigma = 7800\, kg/m^3, \quad P = 1\, kN, \quad E = 207\, GPa,$$
$$S_y = 300\, MPa, \qquad \delta_{\max} = 5\, mm.$$

### *4.2. Test Problem - 2 [31]*

$$\begin{aligned} &\textit{Minimize} \quad f_1(x) = (x_1), \\ &\textit{Minimize} \quad f_2(x) = \frac{1 + x_2}{x_1}, \\ &\textit{Subject to} \quad g_1(x) \equiv x_2 + 9x_1 \geq 6, \\ &\qquad\qquad\quad g_2(x) \equiv -x_2 + 9x_1 \geq 1 \\ &\qquad\qquad\quad 0.1 \leq x_1 \leq 1, \\ &\qquad\qquad\quad 0 \leq x_2 \leq 5. \end{aligned}$$

### *4.3. Test Problem - 3* [25]

The Maximize-Maximize problem [25] is also solved using MODE algorithm.

$$\begin{aligned} &\textit{Maximize} \quad f_1(x) = 3x_1 + x_2 + 1, \\ &\textit{Maximize} \quad f_2(x) = -x_1 + 2x_2 \\ &\textit{Subject to} \quad 0 \leq x_1 \leq 3 \\ &\qquad\qquad\quad 0 \leq x_2 \leq 3 \end{aligned}$$

### *4.4. Test Problem - 4* [31]

$$\begin{aligned} &\textit{Maximize} \quad f_1(x) = 1.1 - x_1, \\ &\textit{Maximize} \quad f_2(x) = 60 - \frac{(1 + x_2)}{x_1} \\ &\textit{Subject to} \quad 0.1 \leq x_1 \leq 1.0 \\ &\qquad\qquad\quad 0 \leq x_2 \leq 5 \end{aligned}$$

### *4.5. Test Problem- 5* [26]

$$
\begin{aligned}
&\textit{Minimize} && f_1(x) = 4x_1^2 + 4x_2^2, \\
&\textit{Minimize} && f_2(x) = (x_1 - 5)^2 + (x_2 - -5)^2, \\
&\textit{Subject to} && C_1(x) = (x_1 - 5)^2 + x_2^2 \le 25, \\
& && C_2(x) = (x_1 - 8)^2 + (x_2 + 3)^2 \ge 7.7, \\
& && 0 \le x_1 \le 5, \\
& && 0 \le x_2 \le 3.
\end{aligned}
$$

### *4.6. Test Problem- 6 [27]*

$$
\begin{aligned}
&\textit{Minimize} && f_1(x) = 2 + (x_1 - 2)^2 + (x_2 - 1)^2, \\
&\textit{Minimize} && f_2(x) = 9x_1 - (x_2 - 1)^2, \\
&\textit{Subject to} && C_1(x) = x_1^2 + x_2^2 \le 225, \\
& && C_2(x) = x_1 - 3x_2 + 10 \le 0, \\
& && -20 \le x_1 \le 20, \\
& && -20 \le x_2 \le 20.
\end{aligned}
$$

## 5. RESULTS & DISCUSSION

The performance of MODE algorithm is tested by applying it to above mentioned benchmark Test problems. Extensive simulation runs are carried out for parametric study. The key parameters of MODE; Crossover constant (CR), Number of population points (NP), Scaling factor (F), Number of generations (Ng) and Penalty parameter (R) are varied over a wide range of their possible values. The results obtained through the simulations are discussed below problem wise.

### *5.1. Test Problem-1*

In Figs. 2 to 8, all the non-dominated solutions obtained for Test problem 1 using MODE approach are plotted. Figure 2 shows the Pareto Optimal front at various values of CR, at a very low value of R. At very low value of R, there is no effect of CR on the Pareto

Optimal front. Both convergence and distribution of all Pareto fronts are good. Pareto Optimal front with CR=0.9 is found to be better than those obtained with CR=0.15 and 0.5 at R=1(Fig. 3). The Pareto Optimal front shown in Fig. 3 with CR=0.15 and 0.5 at R=1 reveals that, convergence is good but spread of solutions is poor. Effect of Penalty parameter, R at a fixed CR value is shown in Figs. 4 & 5. MODE is able to produce a pseudo optimal front at all values of R. Population with large value of R (R=100) shows a poor spread of solution. Also pseudo-optimal fronts seem to approach the true front with increasing value of R (Fig. 4). This may be due to the fact that at very low value of penalty parameter, the front resides in the infeasible region. This is also common in single-objective optimization, because if R-value is chosen as smaller than its optimum value, the penalty effect is less and the resulting optimal front may be infeasible [30].

Fig. 6 shows the effect of NP on the Pareto Optimal front. Pareto front with NP=1000 is found to be better with respect to both convergence and spread on the Pareto Optimal front. Also one of the observations is that with very low value of NP (NP=100), both the convergence and spread of solutions is poor. Fig. 7 shows the effect of constant F on Pareto Optimal front. Randomly generated F is found to give better results. The bar chart representation of the normalized Pareto solutions of both objectives (Weight and Deflection) is shown in Fig. 8. Considering that the objectives can take different ranges of values, the bar chart diagram is plotted with normalized objective values. The diversity in different solutions for each objective can be directly observed from bar-chart representation of the objective functions.

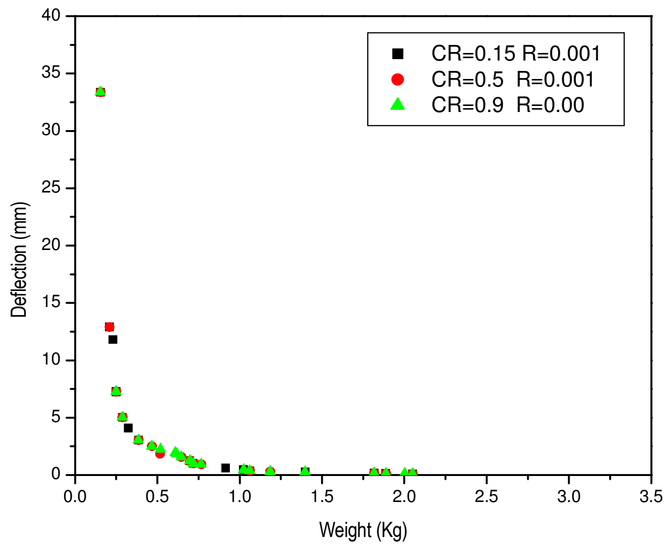

Fig. 2: Effect of CR at R=0.001 on Pareto front

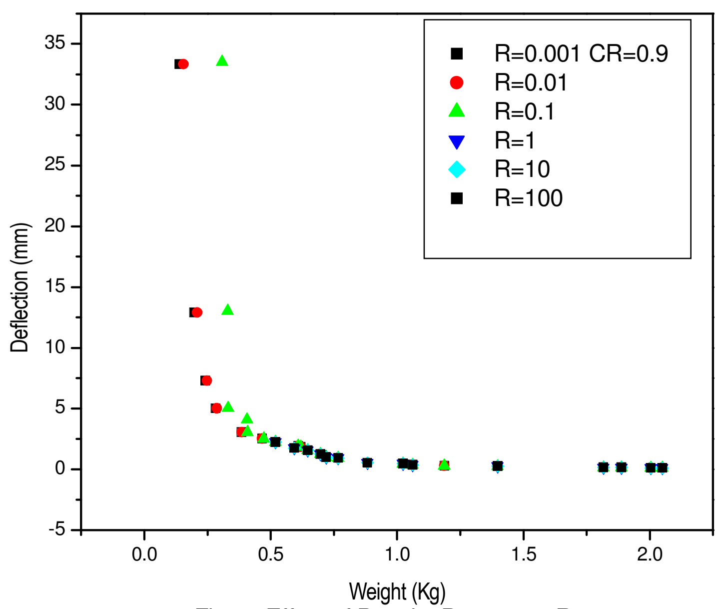

Fig. 3: Effect of Penalty Parameter R

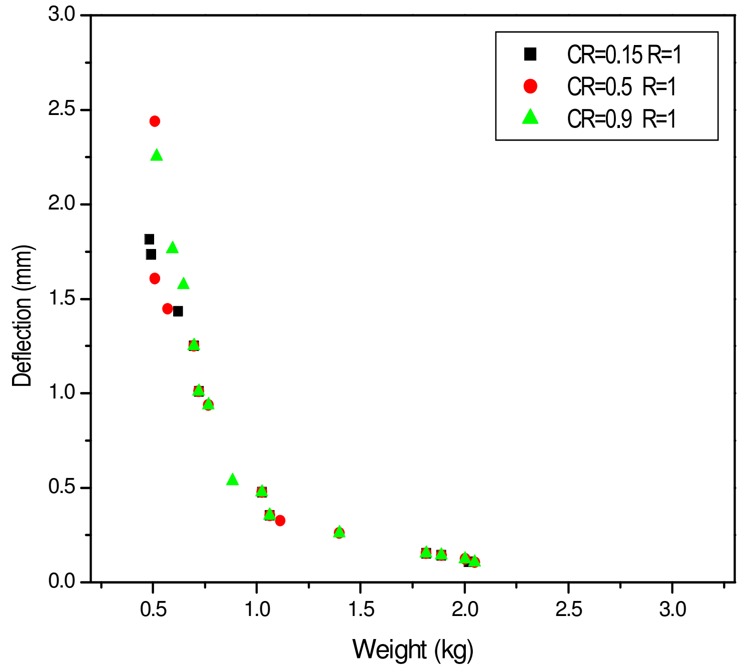


Fig. 4: Effect of CR at R=1

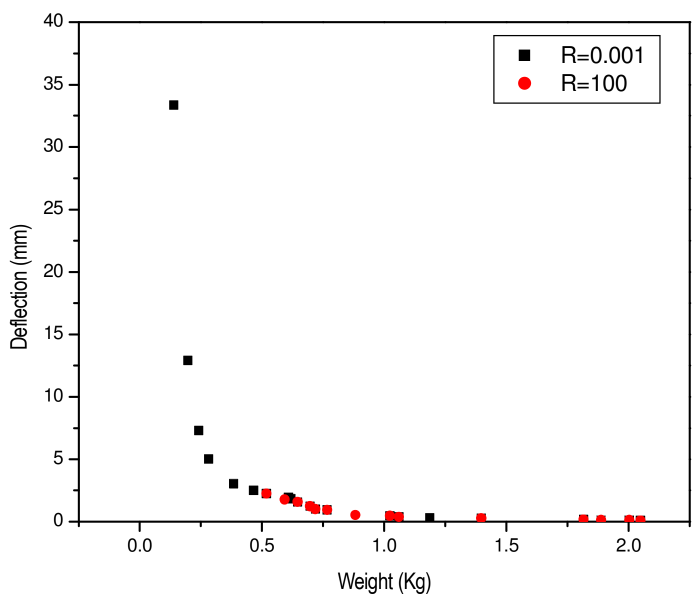


Fig. 5: Effect of Penalty Parameter R

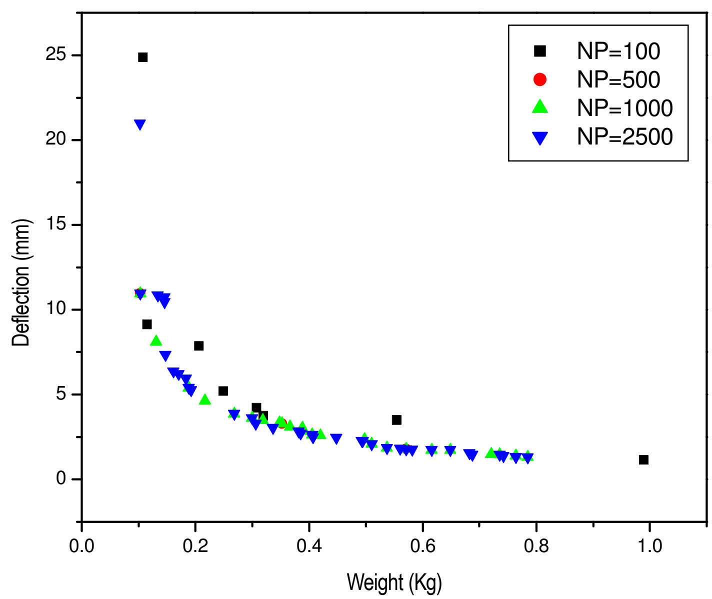

Fig. 6: Effect of NP on Pareto front

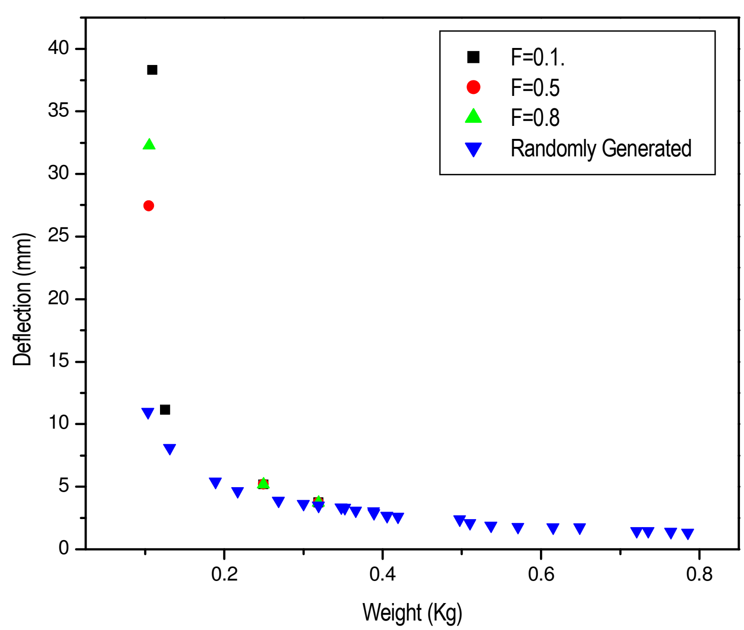

Fig. 7: Effect of constant F on Pareto front

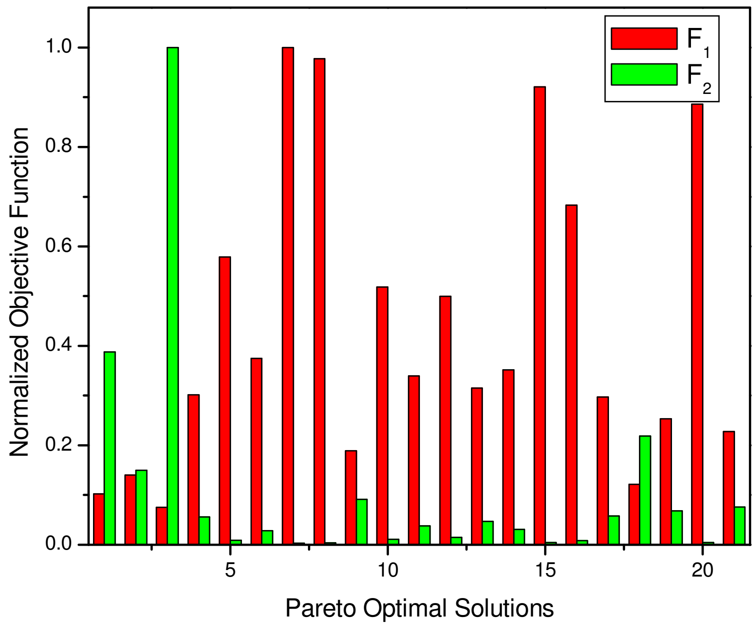

Fig. 8: Bar chart Representation of Pareto front.

### *5.2. Test Problem-2*

In Figs. 9 to 14, all the non-dominated solutions obtained for Test problem 2 using MODE approach are plotted. Fig. 9 shows the Objective space and Pareto Optimal front at various Generations, with CR=0.9, R=0.1 and NP= 1000. Generation after generation, MODE converges to the better Pareto front as shown in the figure. Also, the robustness of MODE can be visualized, as MODE approaches to the true Pareto front at lower generations. Thereafter, even increasing the number of generations, the Pareto front remains same. In Fig. 10, Pareto Optimal front is plotted at various values of CR and NP combinations. Irrespective of CR values, with lesser values of NP (in the range of 100) the performance of MODE is poor at a lesser generation value. This may be due to the fact that at low values of NP, the possibility of getting diversified and well –distributed solutions in the feasible region is very less. As can be seen from Fig. 10, with CR=0.9 and NP=1000, Pareto Optimal front is well distributed as well as converged.

As discussed in Test problem 1, success of MODE approach depends on selection of penalty parameters R1 and R2. To show this effect, we choose different values of R1 and R2. Figs. 11 & 12 show the complete population after 50 generations of MODE for different values of R. The reason for continuing simulations for so long is purely to make sure that a stable population is obtained. Fig. 11 shows that a small penalty parameter cannot find all feasible solutions even after several generations. Since penalty terms are added to each objective function, the resulting penalized objective functions may form a Pareto optimal front different from the true Pareto-optimal front, particularly if the chosen penalty parameter values are not adequate. It also reveals from Figs. 12 & 13 that Pseudo Pareto-Optimal fronts seem to approach to the true front with increasing value of R but the Population with a large R (R=100) shows a poor spread of solutions. These results are consistent with the results obtained in Test problem 1. Fig. 14 shows the bar chart representation of the objective functions.

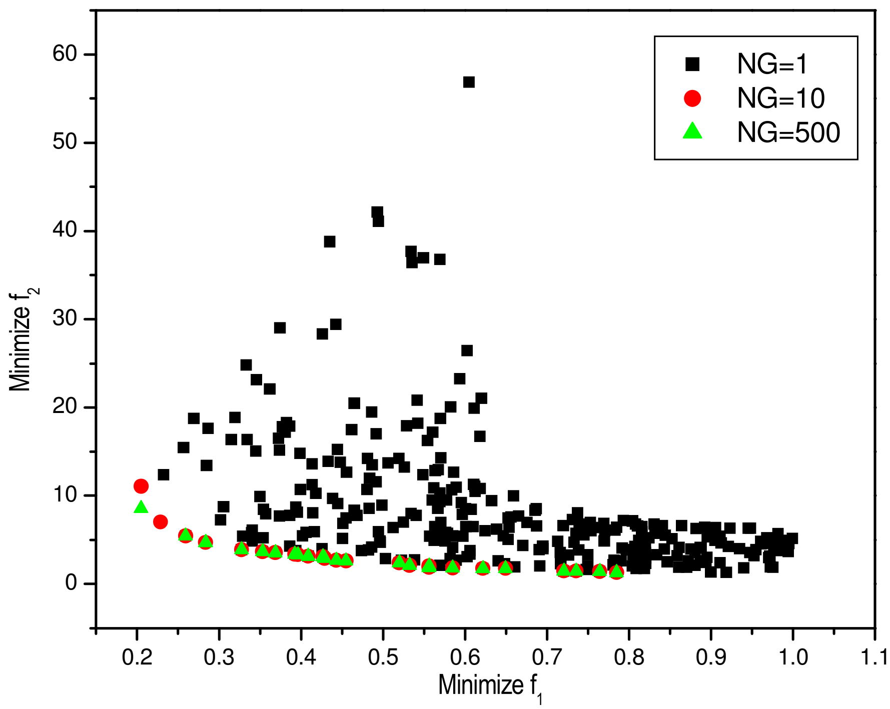

Fig. 9: Pareto front at various Generations with CR=0.9

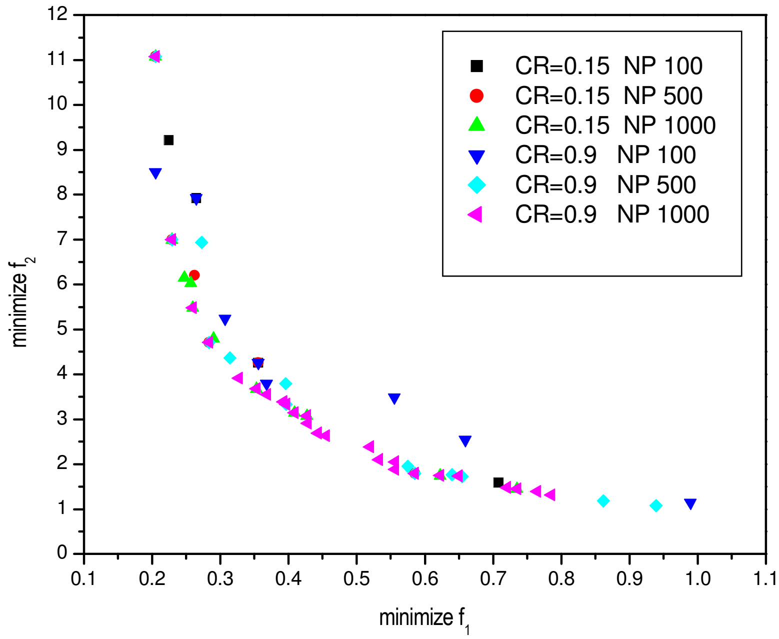

Fig. 10: Pareto front at varied values of NP and CR

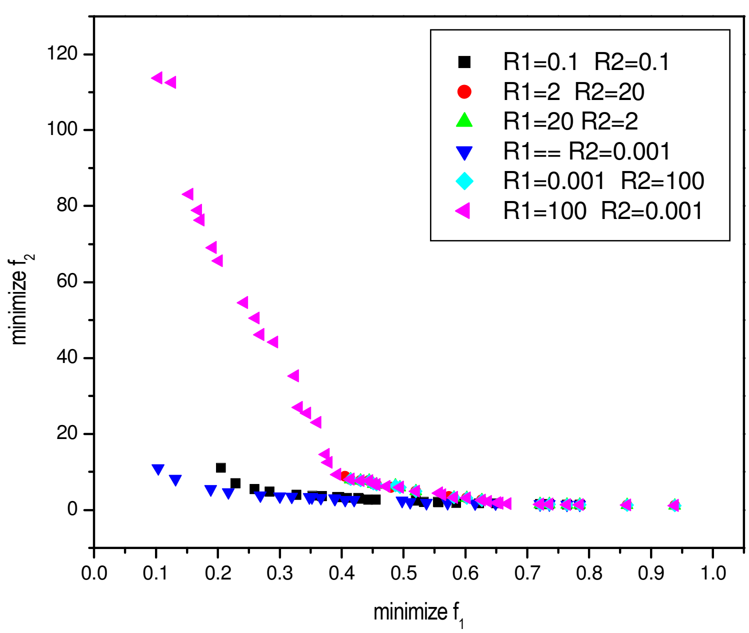

Fig. 11: Pareto front at varied penalty parameter values

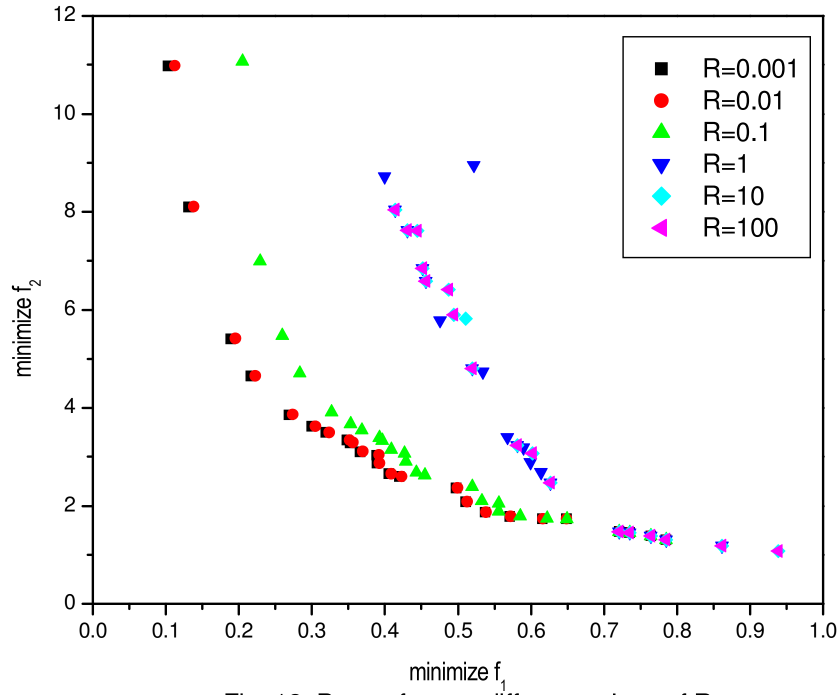

Fig. 12: Pareto front at different values of R

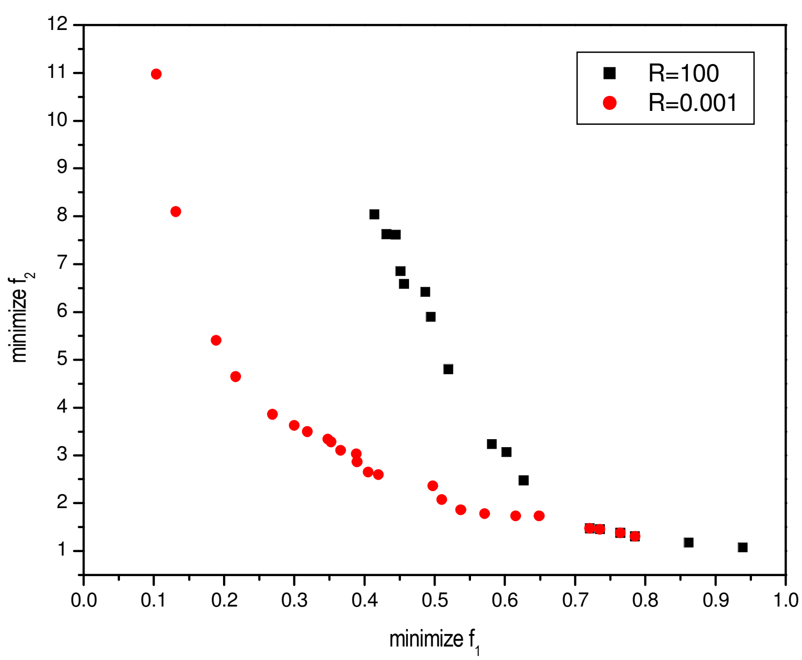

Fig. 13: Pareto front at various R values

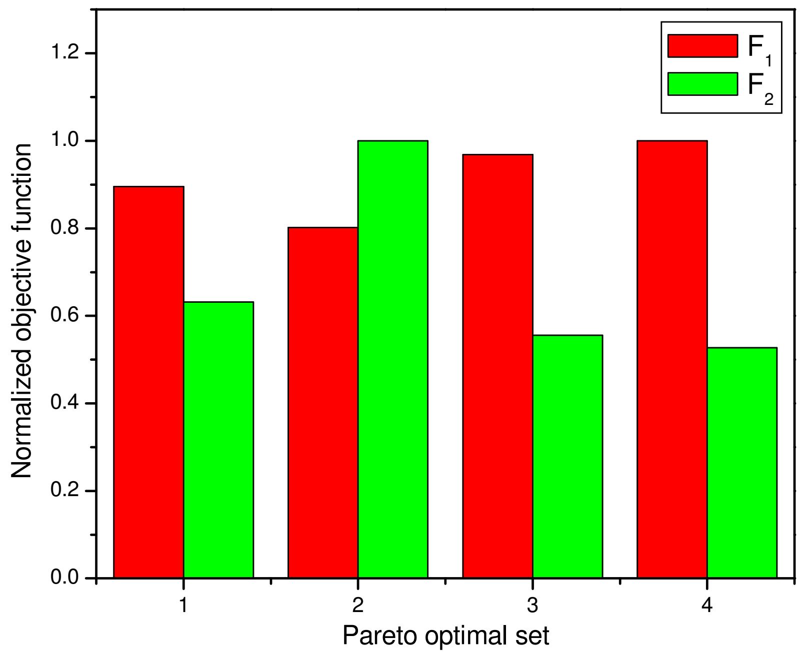

Fig. 14: Bar Chart Representation

### *5.3. Test Problem-3*

In Figs. 15 to 18, all the non-dominated solutions obtained for unconstrained Test problem 3 using MODE approach are plotted. Fig. 15 shows the Pareto Optimal front at various Generations and the objective space. These fronts are plotted using the parametric values as CR=0.15 and NP= 500. In the objective space, all the points are distributed evenly. As has been the case with the previous Test problems, in this case also, MODE converges to the better Pareto front. This also proves the robustness of MODE for Maximize-maximize problems with two objectives. In Fig. 16, Pareto front is plotted at various values of CR at fixed generation. MODE is robust enough to give the same Pareto Optimal front at all CR values. Fig. 17 shows the population after 100 generations and with CR=0.15 and various values of NP. MODE converges to the same Optimal front at any value of NP. The bar chart representation of the normalized Pareto solutions of both objectives is shown in Fig. 18.

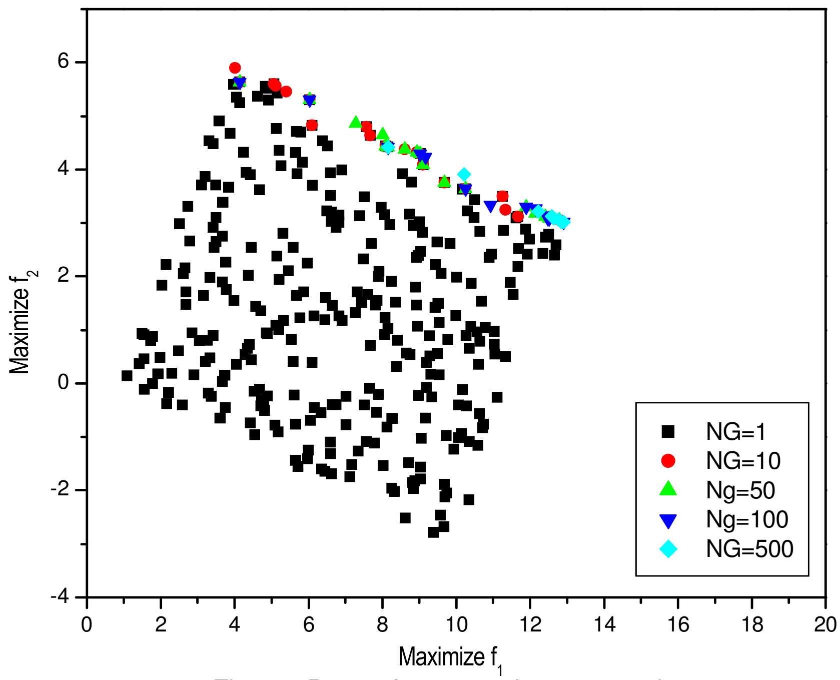

Fig. 15. Pareto front at various generations

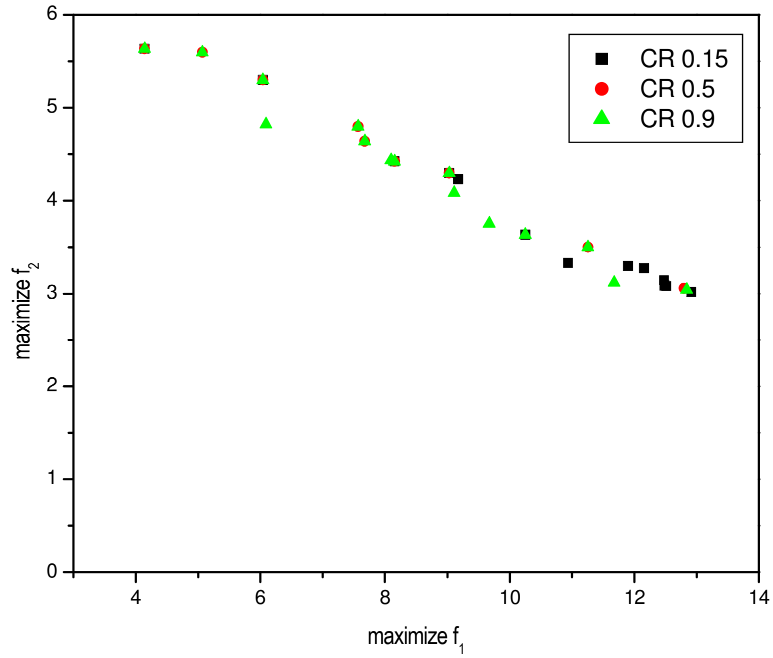

Fig. 16: Pareto front at various values of CR

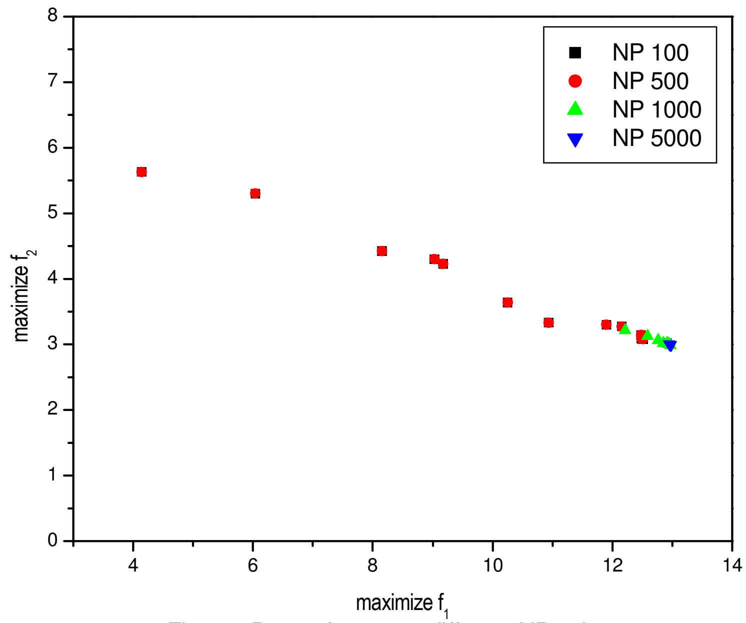

Fig. 17: Pareto front at at different NP values

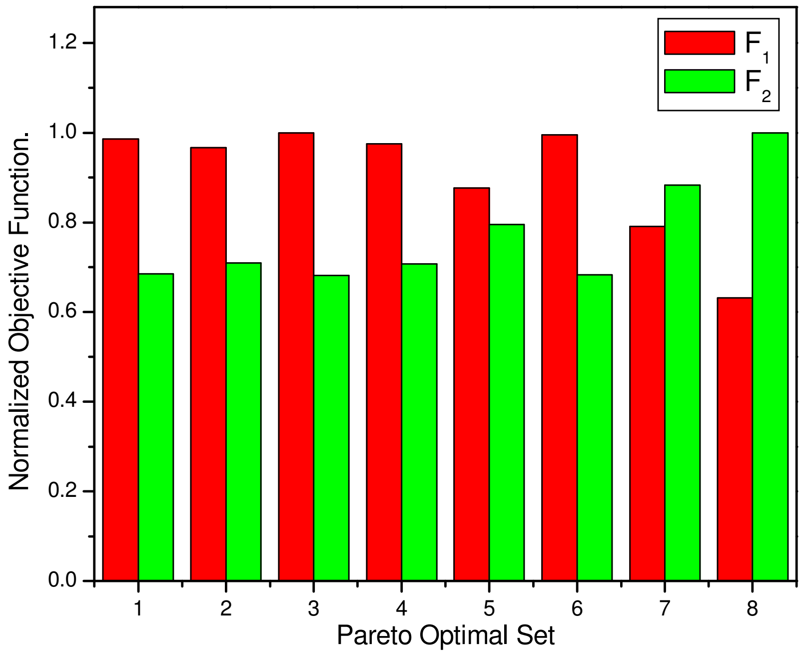

Fig. 18: Bar- Chart Representation

### *5.4. Test Problem-4*

In Figs. 19 to 21, all the non-dominated solutions obtained for Test problem 4 using MODE approach are plotted. In Fig. 19, Pareto front is plotted at various values of CR at fixed generation. For this case too, the same Pareto Optimal front is obtained at all CR values with few exceptions. Fig. 20 shows the Pareto Optimal front at various Generations, with CR=0.9 and NP= 1000. The Pareto Optimal front is plotted at generation 1, 10, 100 and 1000. The non-dominated set of solutions goes on converging generation after generation. The points shown at generation 1 show the feasible objective space for the Maximize-Maximize Test problem given in section 4.4. The exact number of non-dominated solutions for above-mentioned problem in generations 1, 10, 100 and 1000 is 298, 10, 8 and 2 respectively. In this case also in each generation, MODE converges to the better Pareto front. This also proves the robustness of MODE for Maximize-maximize problems with two objectives. The bar chart representation of the normalized Pareto solutions of both objectives is shown in Fig. 21.

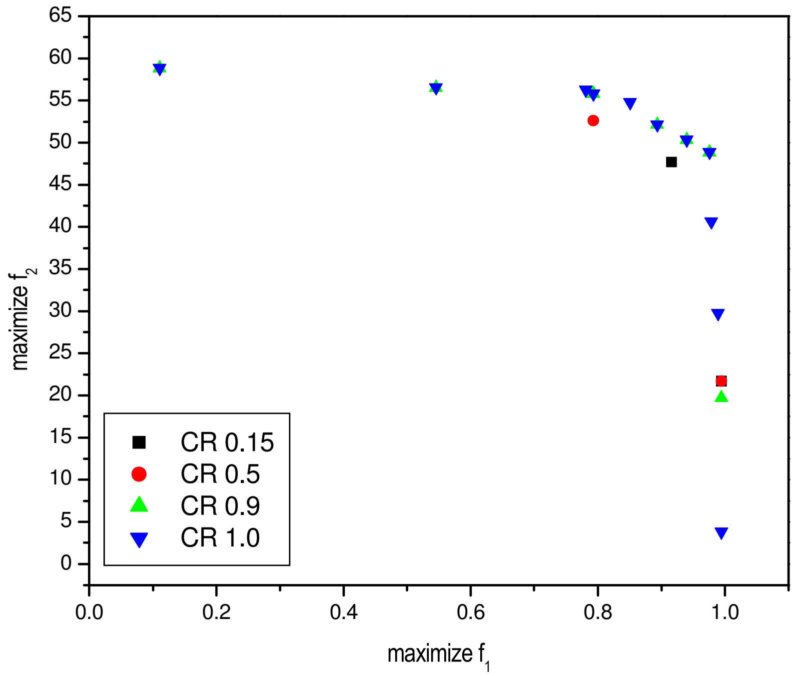


Fig. 19: Pareto front at various CR values

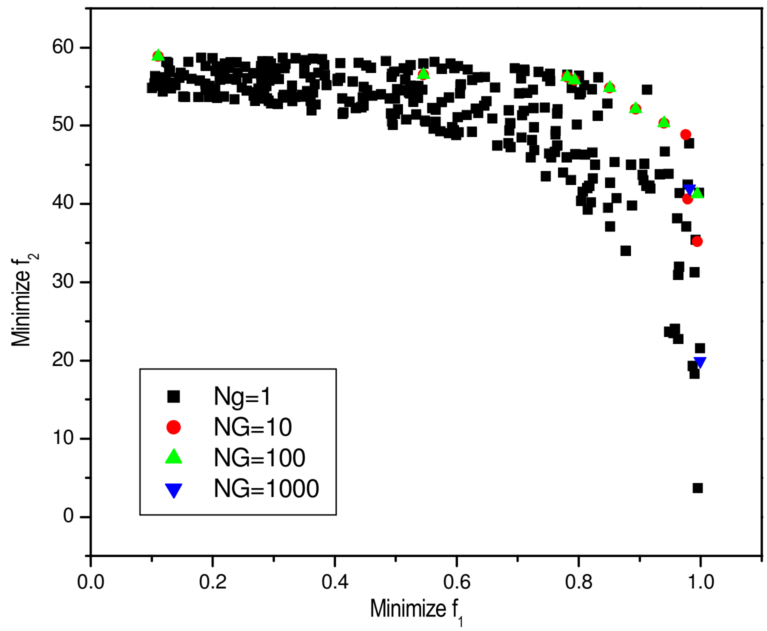


Fig. 20: Pareto front at various generations

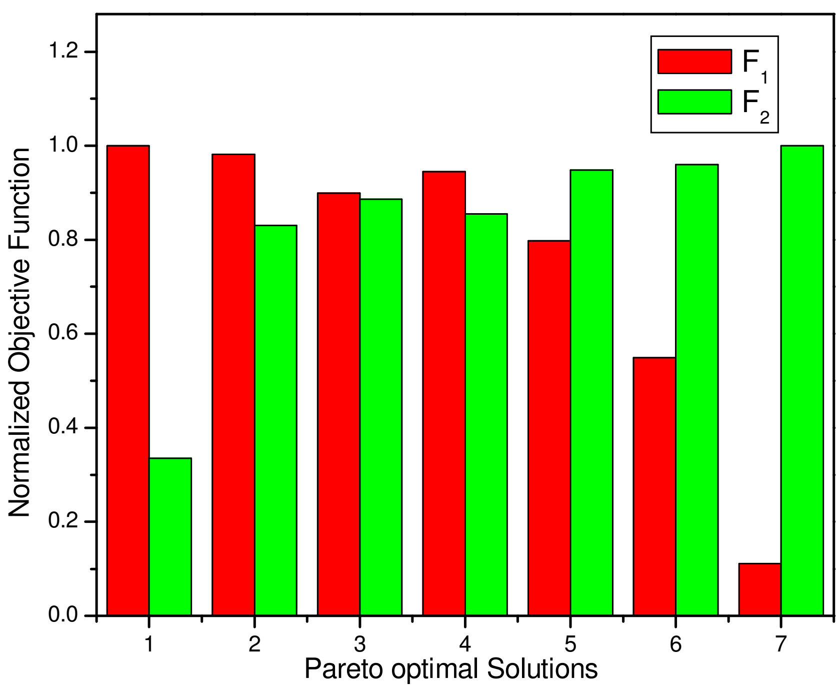


Fig. 21: Bar- Chart Representation

### *5.5. Test Problem-5*

Binh and Korn [26] introduced the two variable constrained problem (BNH) as given in section 4.5. Figs. 22 to 26 show the Pareto Optimal front for two variable constrained Minimize-minimize BNH test problem. Fig. 22 shows the effect of CR on the Pareto front. MODE is found to converge to the same front at various values of CR. But the number of non-dominated solutions is found to be increasing with increasing the value of CR. The non-dominated solutions at the CR value of 0.15, 0.5 and 0.9 for BNH problem are 101, 136 and 149 respectively after 500 generations. Pareto Optimal front is plotted with various NP values after 500 generations in Fig. 23. MODE is tested with various NP values and results with NP 100, 500 and 1000 are shown in Fig. 23. MODE is found to converge to the same front at any value of NP. However the number of non-dominated solutions in the Pareto set is found to vary with NP values. Number of non-dominated solutions for NP 100, 500 and 1000 is 107, 98 and 147 respectively. It is interesting to note that with NP values of 100, the number of non-dominated solutions is 107. The objective space and the Pareto Optimal front for BNH problem at various generations is shown in Fig. 22. MODE is found to converge to true Pareto Optimal front at generation value of 10. After 500 generations although Pareto front is same as that at generation 10, it contains 2 non-dominated solutions less than that at generation 10. Effect of constant F on Pareto Optimal front is shown in Fig. 25. MODE converges to the true Pareto front irrespective of the value of F in the range. The number of non-dominated solutions is found to be same at all values of F including the random generation of F. Fig. 26 shows the effect of Penalty parameter on the Pareto front. As penalty terms are added to each objective function, the resulting Pareto optimal front is different from the true Pareto Optimal front. Relaxing the constraints (low R value) moves Pareto Optimal front to infeasible region, while increasing the value of Penalty parameter move the front into a feasible objective space. MODE algorithm is found to converge to only 2 optimal solutions with R=50.

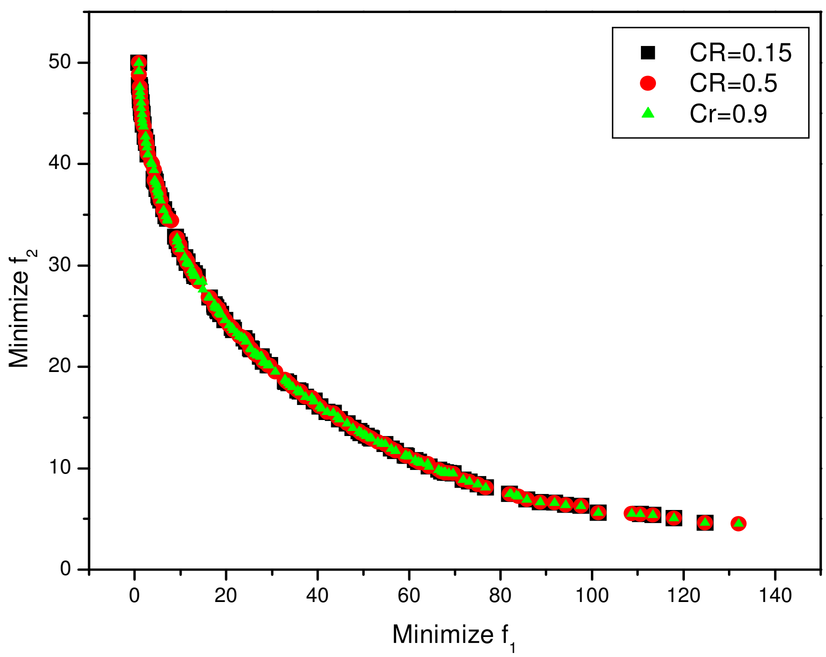

Fig. 22: BNH Problem Pareto front at various CR values

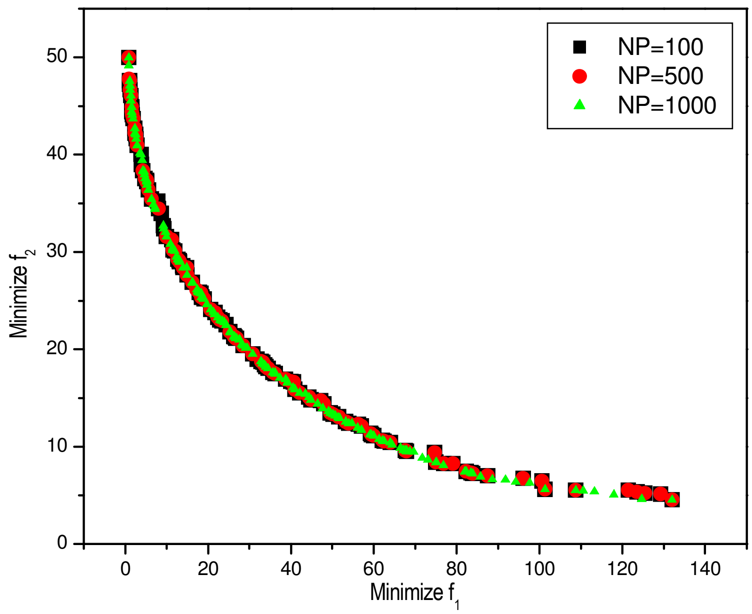


Fig. 23: BNH Problem Pareto front at various NP

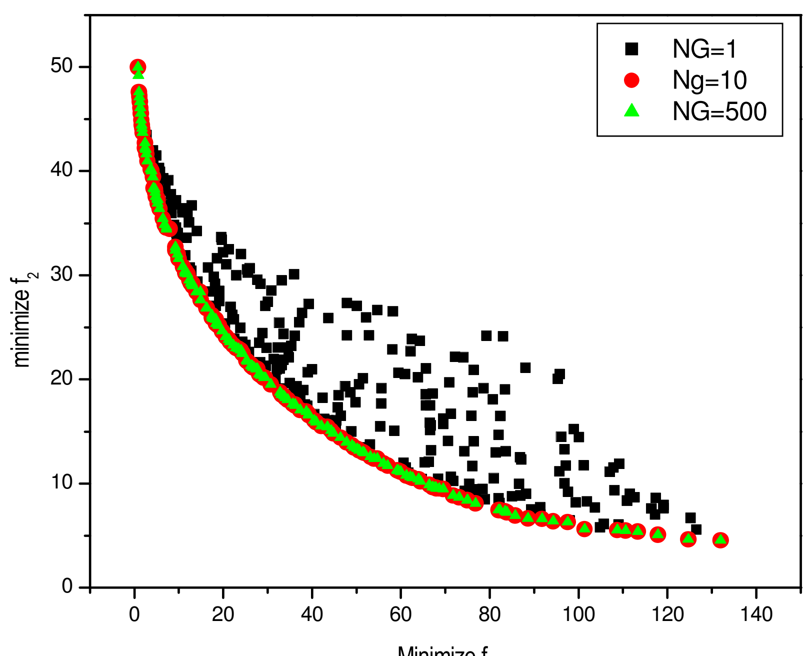


Fig. 24: BNH Pareto front at various generations

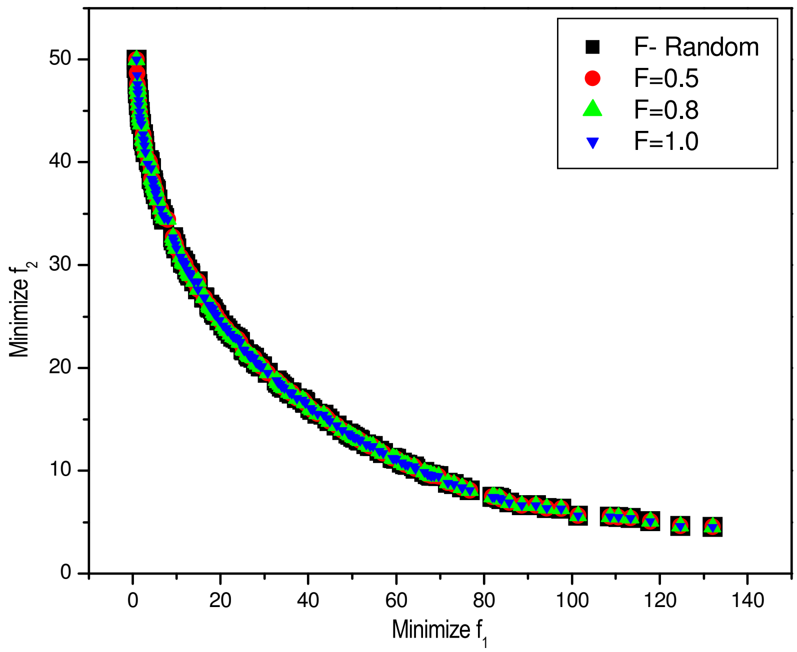

Fig. 25: BNH Pareto Front at various F values

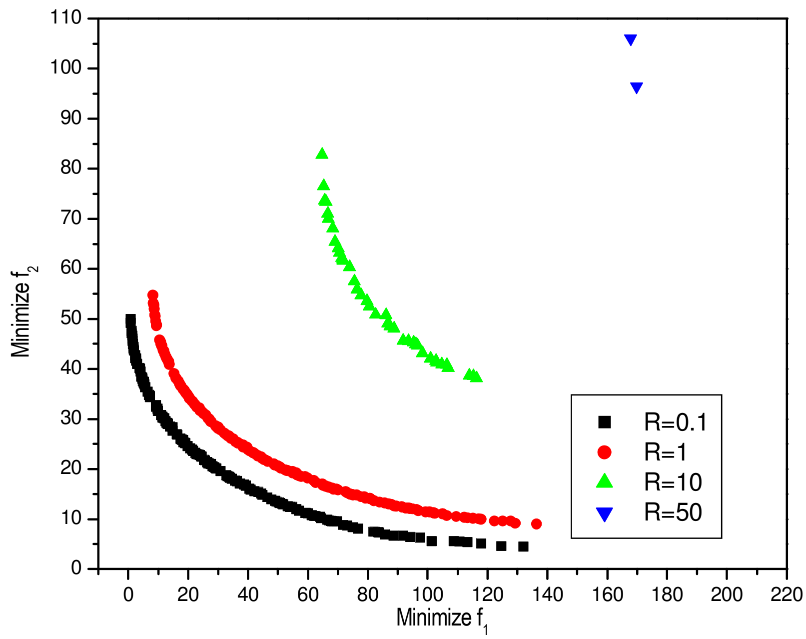

Fig. 26: BNH Pareto front at various Penalty Parameters

### *5.6. Test Problem-6*

This test problem (SRN) is borrowed from Chankong and Haimes [27]. Figs. 27 to 31 show the Pareto Optimal front for SRN problem at various parameter values. As has been the case with earlier problems discussed above, MODE converges to the same optimal front at all values of CR within range of 0 to 1 (Fig. 27). Fig. 28 shows the SRN Pareto Optimal front at various NP values. Pareto front is same in this case with few exceptions at NP=100. The reason for such trade-off in Pareto front is discussed in section 3.3.2. The objective function space and the Pareto optimal front at various generations are shown in Fig. 29. These results also match with the results discussed above. Fig. 30 shows the Pareto Optimal front with various values of F. Pareto front is rich with respect to number of non-dominated solutions in the dominant objective feasible space, which can be seen from Fig. 29. Effect of R on SRN test problem is shown in Fig. 31. In this case also, increase in the Penalty Parameter pushes the Optimal Pareto front in the feasible region away from the true front.

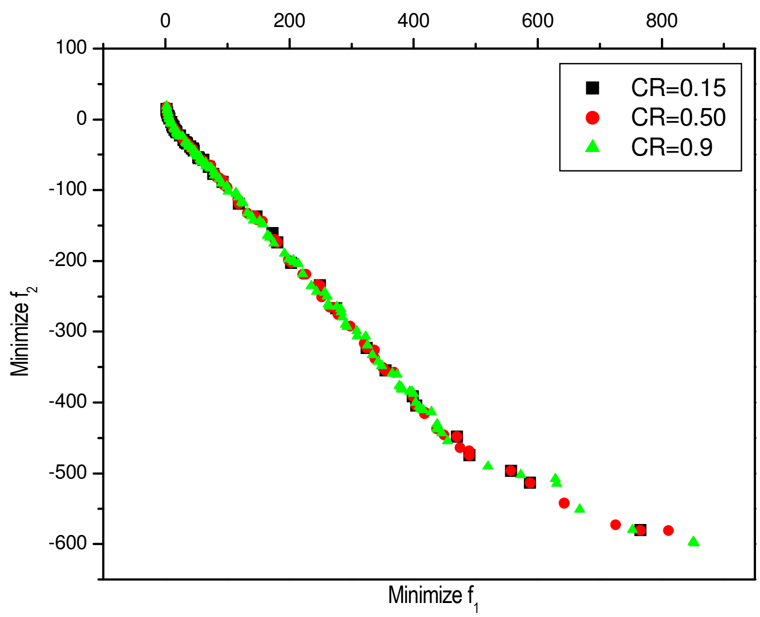


Fig. 27: SRN Pareto front at various values of CR

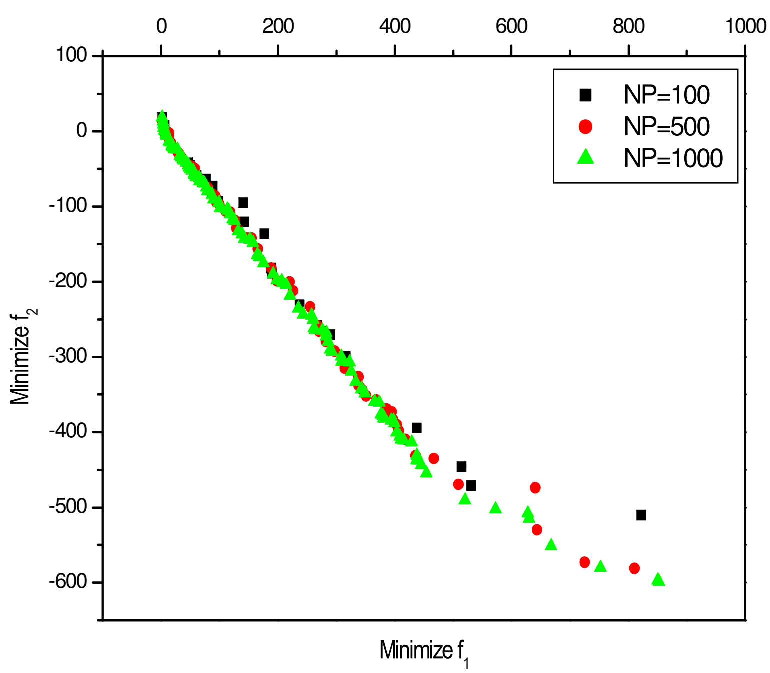


Fig. 28: SRN Pareto front at various number of populations

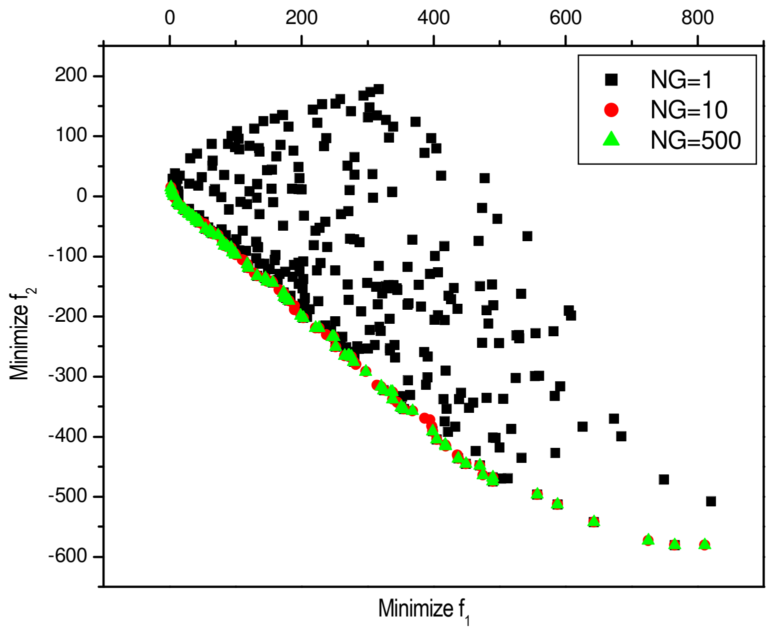


Fig. 29: SRN Pareto Front at various generations

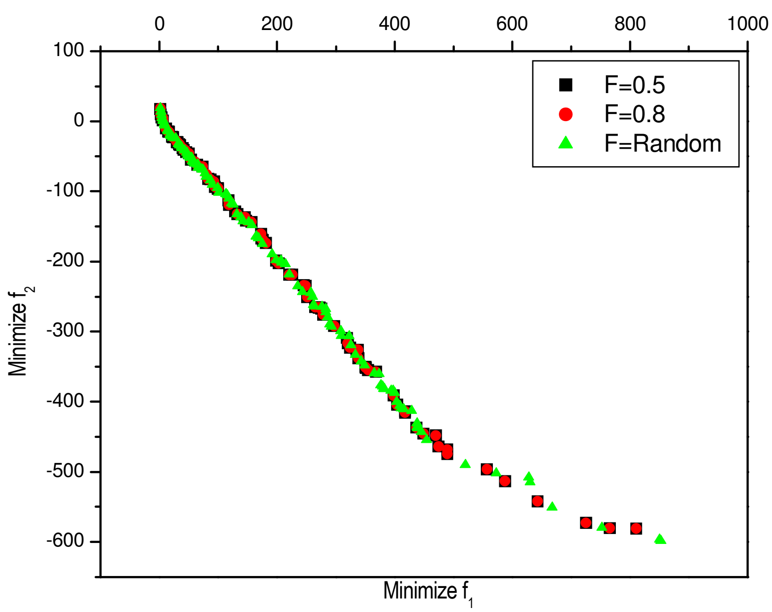


Fig. 30: SRN Pareto front at various F values

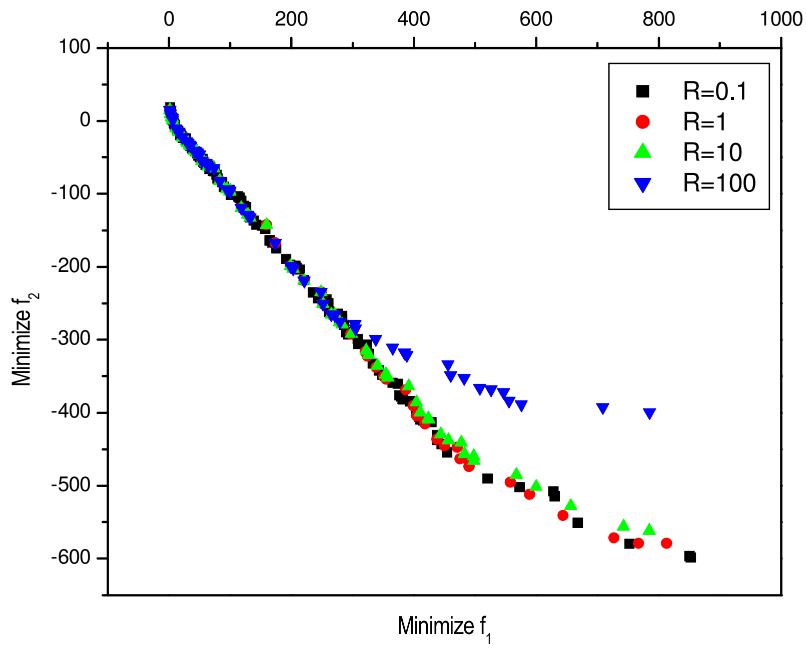

Fig. 31: SRN Pareto front at various R values

## 6. CONCLUSIONS

MODE algorithm is applied to six different benchmark test problems for validating its robustness and performance. MODE is found to handle all kinds of MO problems with and without constraints. MODE is already found to give the exact results in terms of optimum objective function values with respect to NSGA [22, 23]. Also both NSGA and MODE are found to follow the same Pareto Optimal front. In this study we observed the robustness of MODE with respect to its key parameters, i.e., CR, NP, F, and Ng. Generation after generation, MODE converges to the better Pareto Optimal front. MODE is robust enough to give the same Pareto Optimal front for all CR values. F is found to have no effect on the Pareto front.

Pseudo Pareto-Optimal fronts seem to approach to the true front with increasing value of R but the Population with a large R (R=100) shows a poor spread of solutions. This may be due to the fact that at very low value of penalty parameter, the front resides in the infeasible region. If R-value is chosen as smaller than its optimum value, then the penalty effect is less and the resulting optimal front may be infeasible. With very low value of NP (NP=100), both the convergence and spread of solutions is found to be poor. This may be due to the fact that at low values of NP, the probability of getting diversified and well-distributed solutions in the feasible objective function region is very less. Bar chart representation of normalized Pareto solutions is a useful way to represent different non-dominated solutions. The diversity in different solutions for each objective can be directly observed from bar-chart representation of the objective functions. With this representation, user can easily compare and select the solutions according to his need due to the wide range of available solutions.

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