VLMOPSO Technical Report

Mathematical Functions: Using Mutation in Both MOPSO and VLMOPSO

1- Rosen-Griewanks-Rastrigin:

Objectives:
f(1)=-RosenbrockObjFun(x);
f(2)=Griewanks(x);
f(3)=-Rastrigin(x);

Search Space: [-600 600]

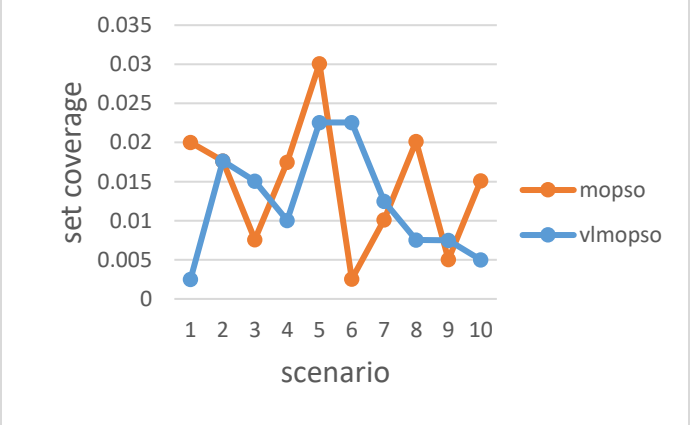
Lower Length: 1 population Size: 200 Iterations: 200
Higher Length: 20

Results:

Set coverage:

VLMOPSO Vs MOPSO

C(vl-mopso,mopso)	C(mopso,vl-mopso)
0.002506	0.02
0.01763	0.01763
0.01508	0.007595
0.01003	0.0175
0.02256	0.03008
0.02256	0.002532
0.0125	0.0101
0.007538	0.02015
0.0075	0.005025
0.005013	0.01511
T Test:	0.529852

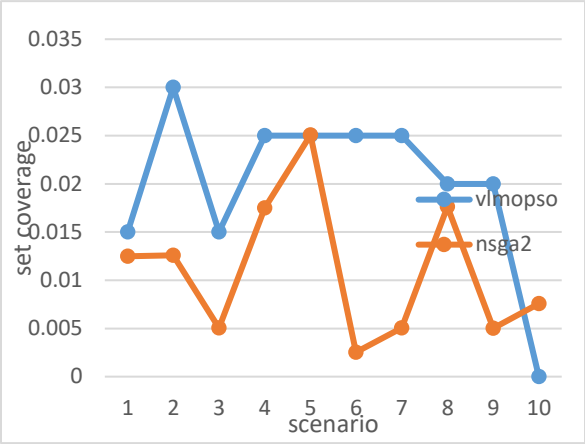


As we see there is no significant difference

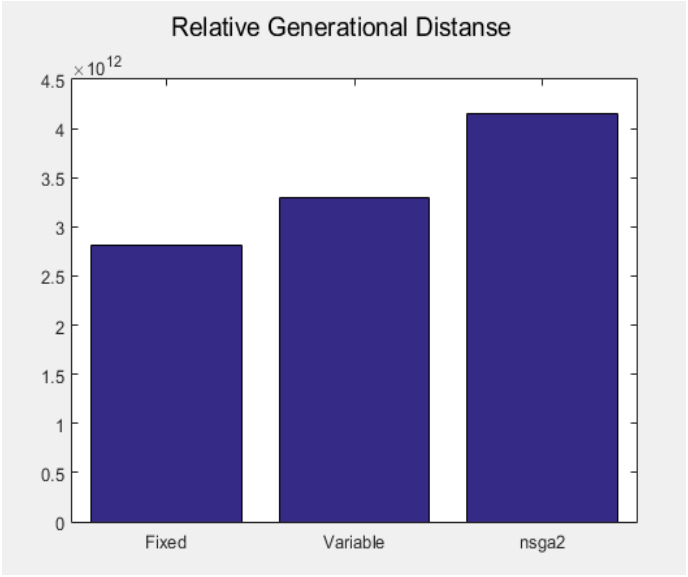
VLMOPSO vs NSGA2

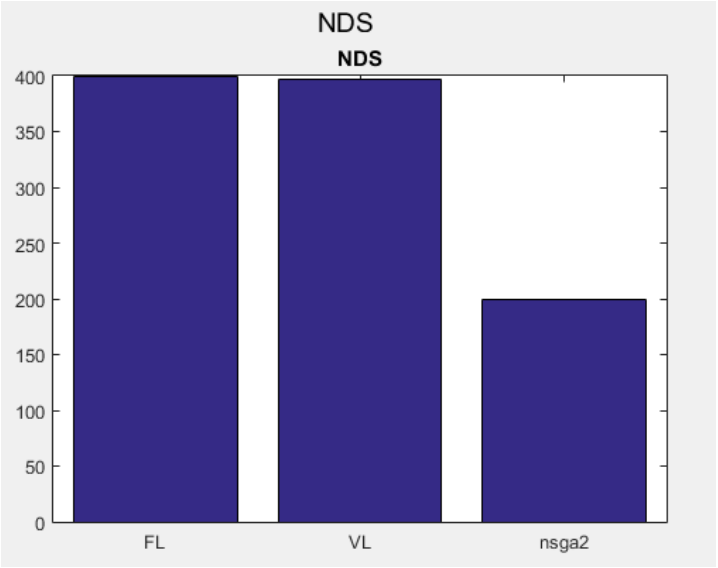
C(vl-mopso,nsga2)	C(nsga2,vl-mopso)
0.015	0.0125
0.03	0.01259

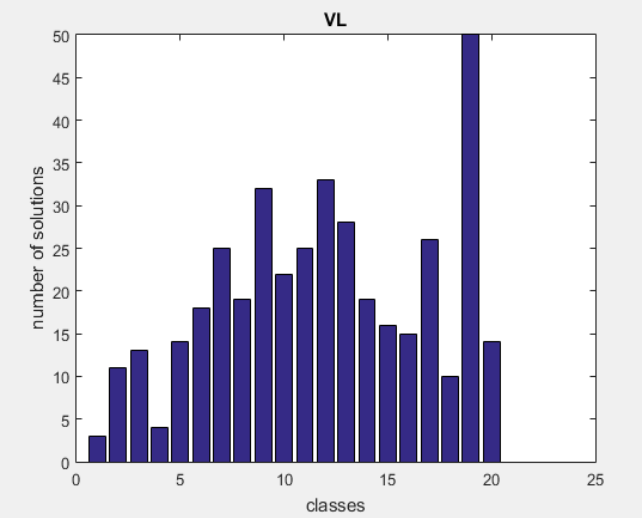
0.015	0.005063
0.025	0.0175
0.025	0.02506
0.025	0.002532
0.025	0.005051
0.02	0.01763
0.02	0.005025
0	0.007557
T Test:	0.017409

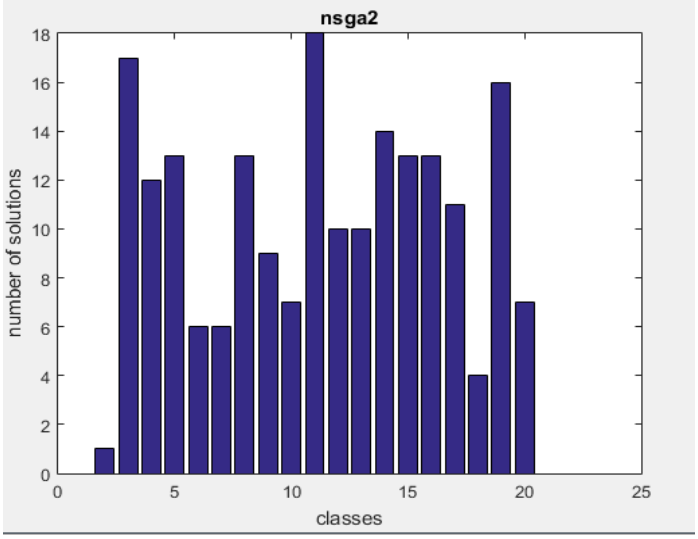


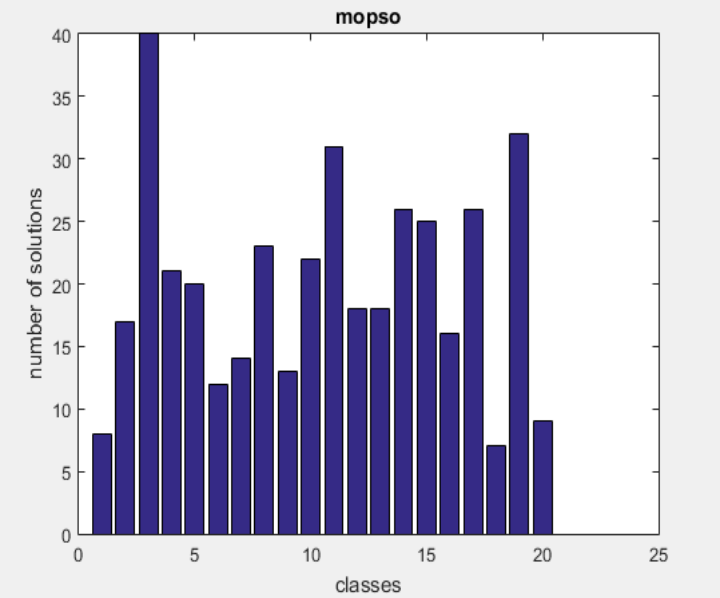
There is significant difference and vlmopso is better than nsga2

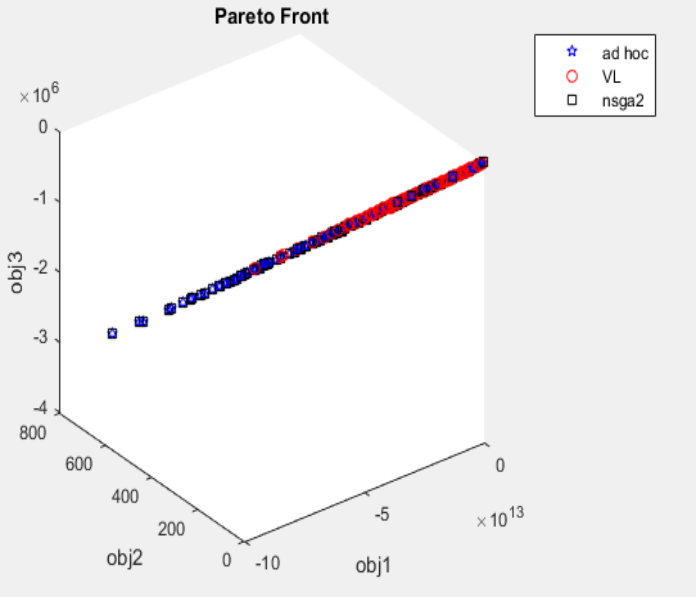

Relative Generational Distanse
×10^12
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
Fixed
Variable
nsga2


NDS
NDS
400
350
300
250
200
150
100
50
0
FL
VL
nsga2


VL
number of solutions
classes


nsga2
number of solutions
classes


mopso
number of solutions
classes


Pareto Front
ad hoc
VL
nsga2
×10^6
obj3
obj2
obj1
×10^13

2- Rosen-Rastrigin

Objectives:

f(1)=RosenbrockObjFun(x);
f(2)=-Rastrigin(x);

Search Space: [-5.12 5.12]

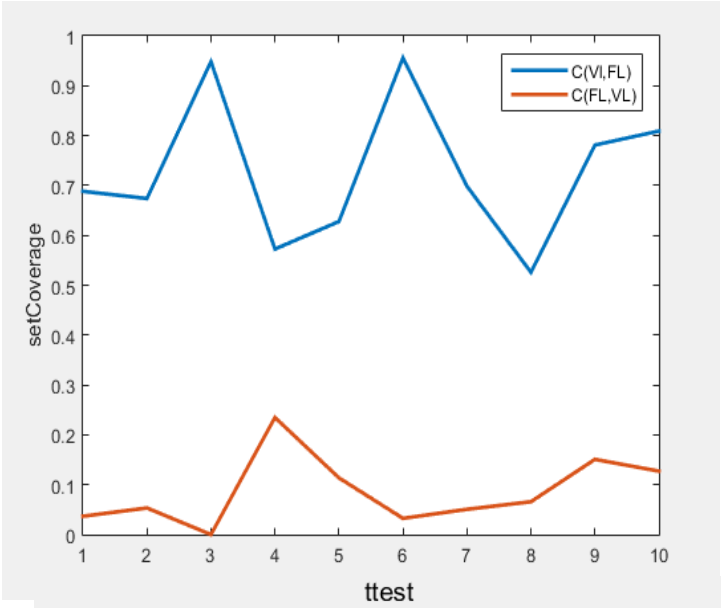
Lower Length: 1 population Size: 500 Iterations: 200
Higher Length: 30

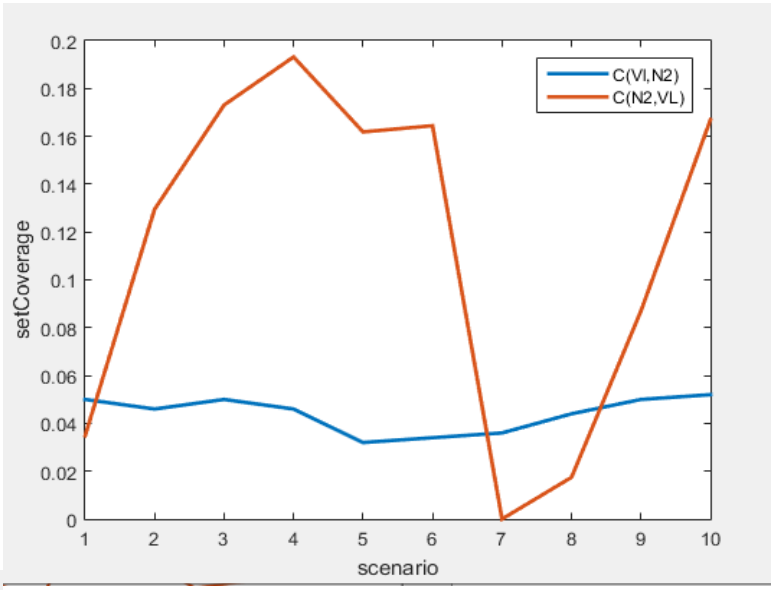
Results:

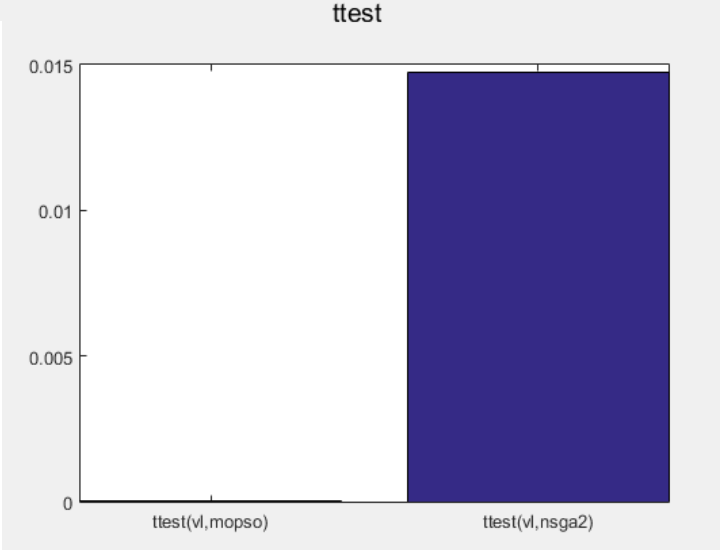
Set coverage:
VL = VLMOPSO

FL= MOPSO

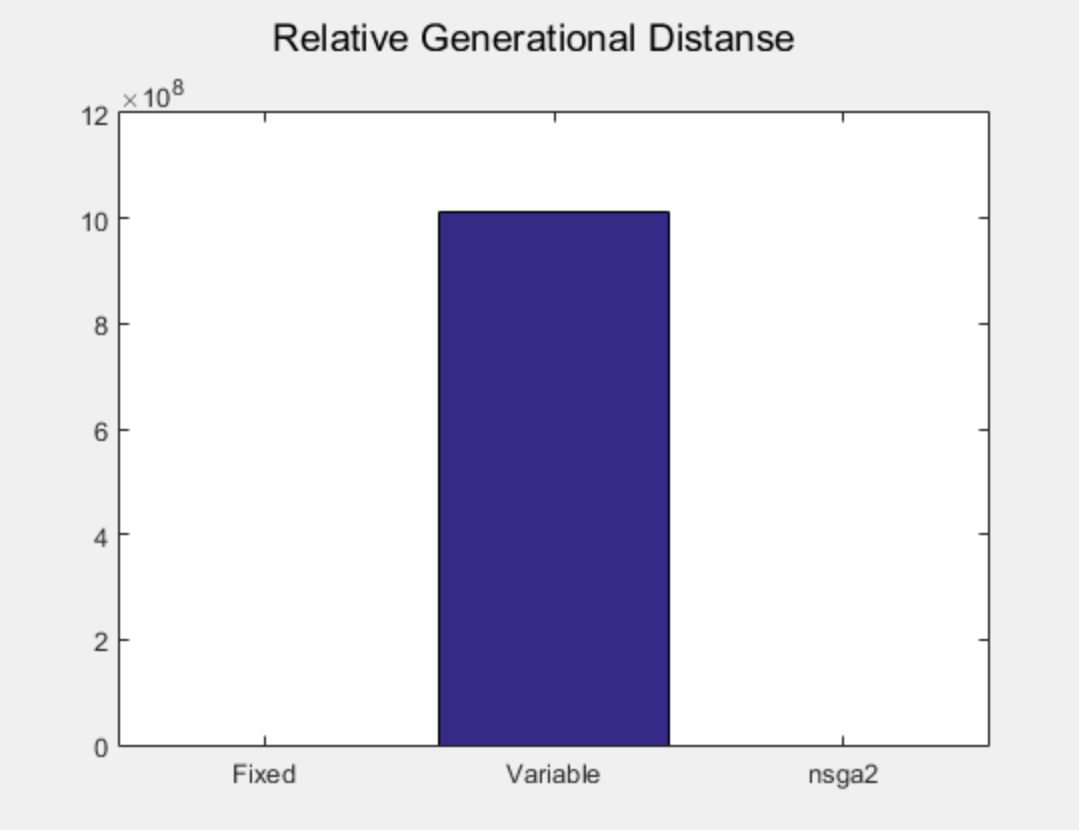
N2=NSGA2

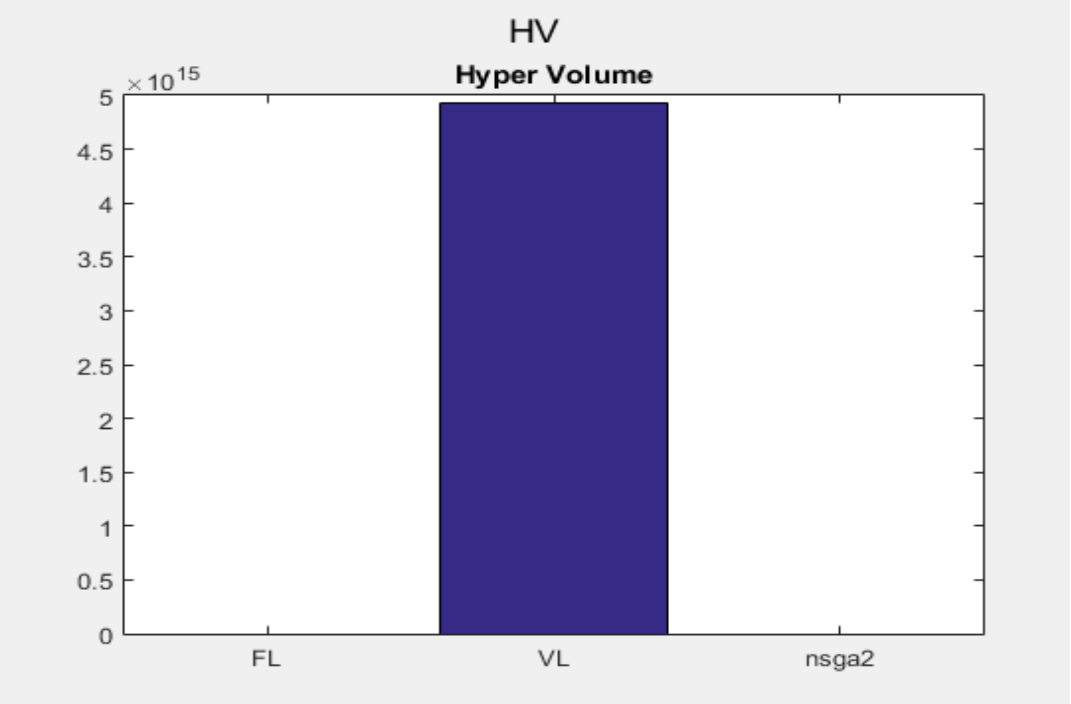


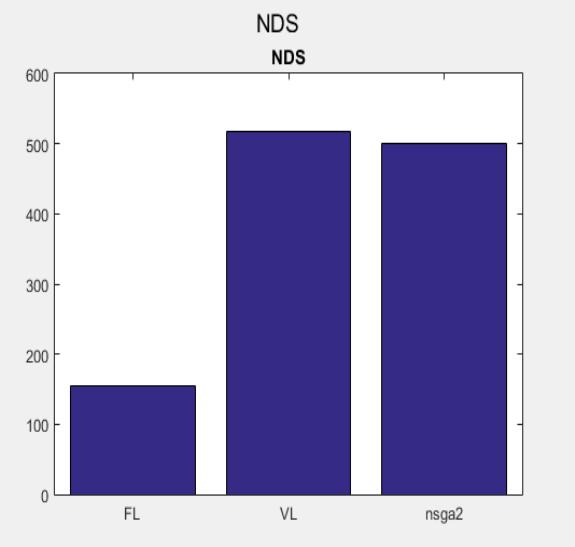


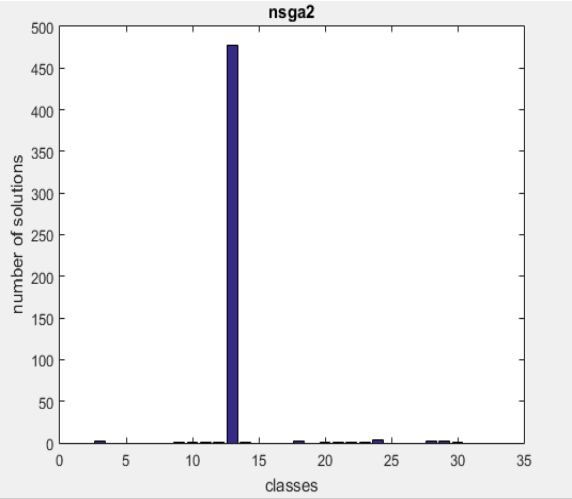


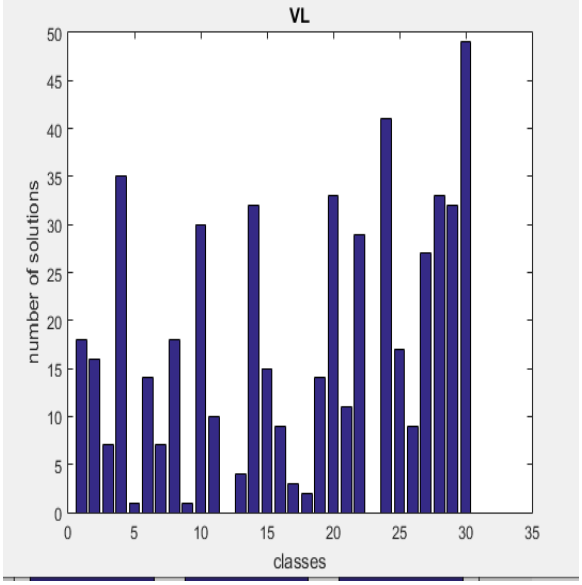
There is significant Difference

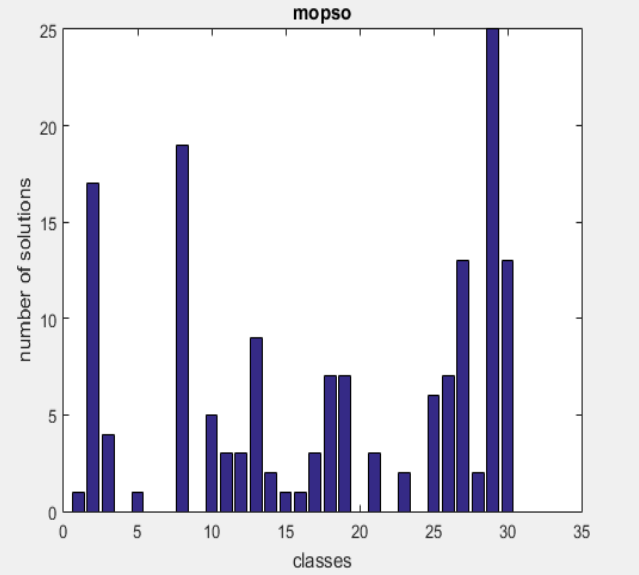

Relative Generational Distanse
×10^8
12
10
8
6
4
2
0
Fixed
Variable
nsga2

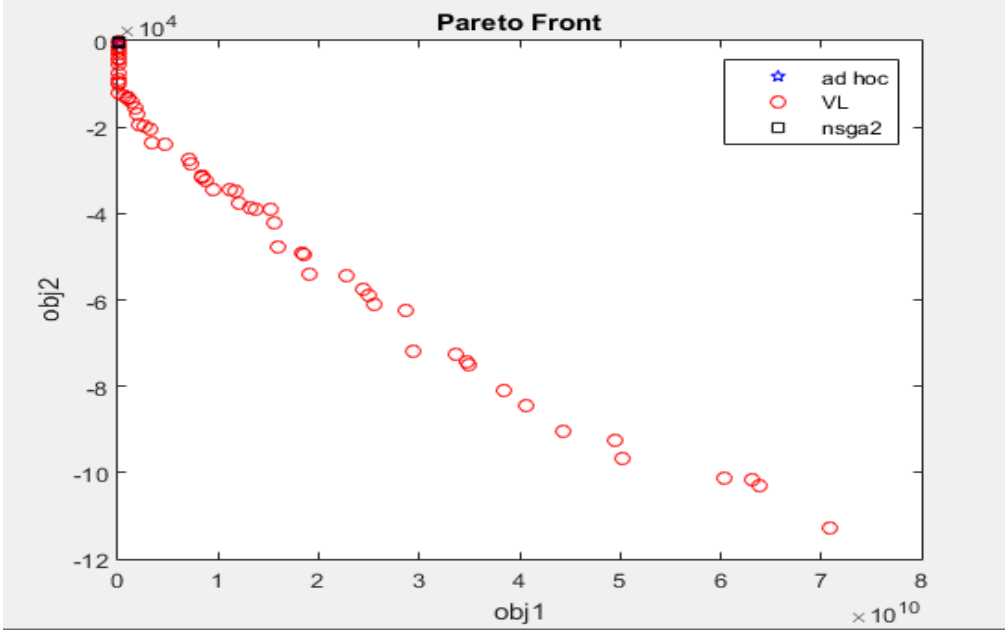

HV
Hyper Volume
×10^15
5
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
FL
VL
nsga2


NDS
NDS
600
500
400
300
200
100
0
FL
VL
nsga2


nsga2
number of solutions
classes


VL
number of solutions
classes


mopso
number of solutions
classes


Pareto Front
ad hoc
VL
nsga2
obj2
obj1

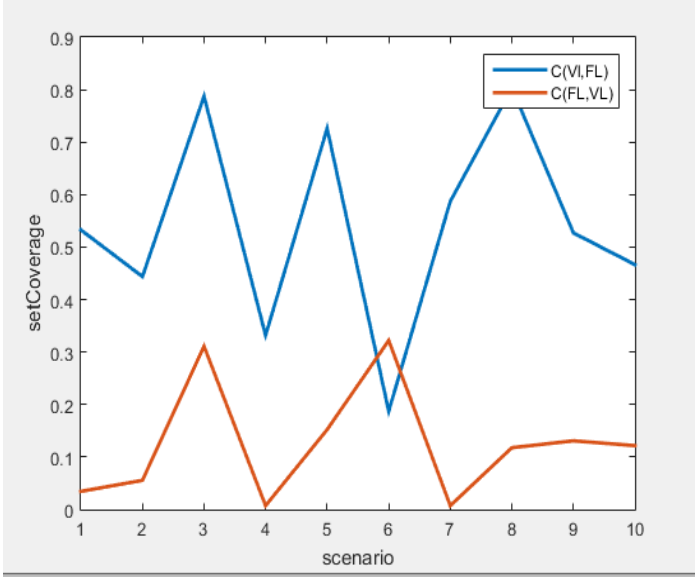
3- levy-stybtang-powell

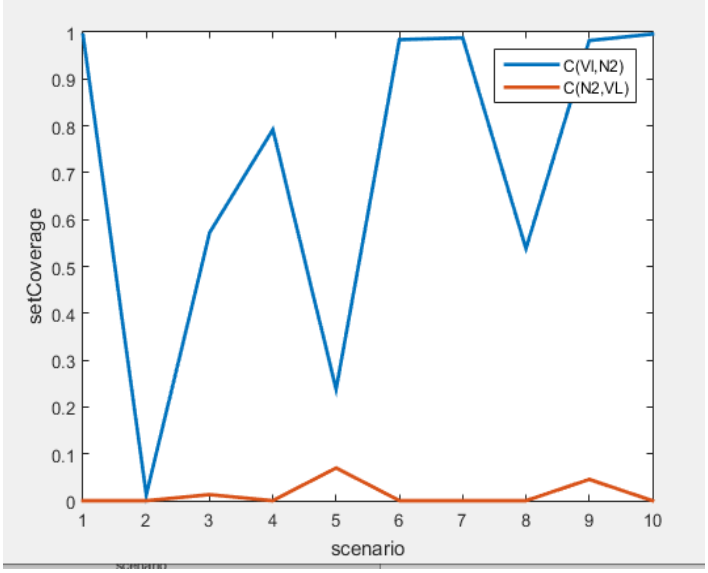
f(1)=levy(x);
f(2)=powell(x);
f(3)=stybtang(x); stybtang function is decreasing as length increases

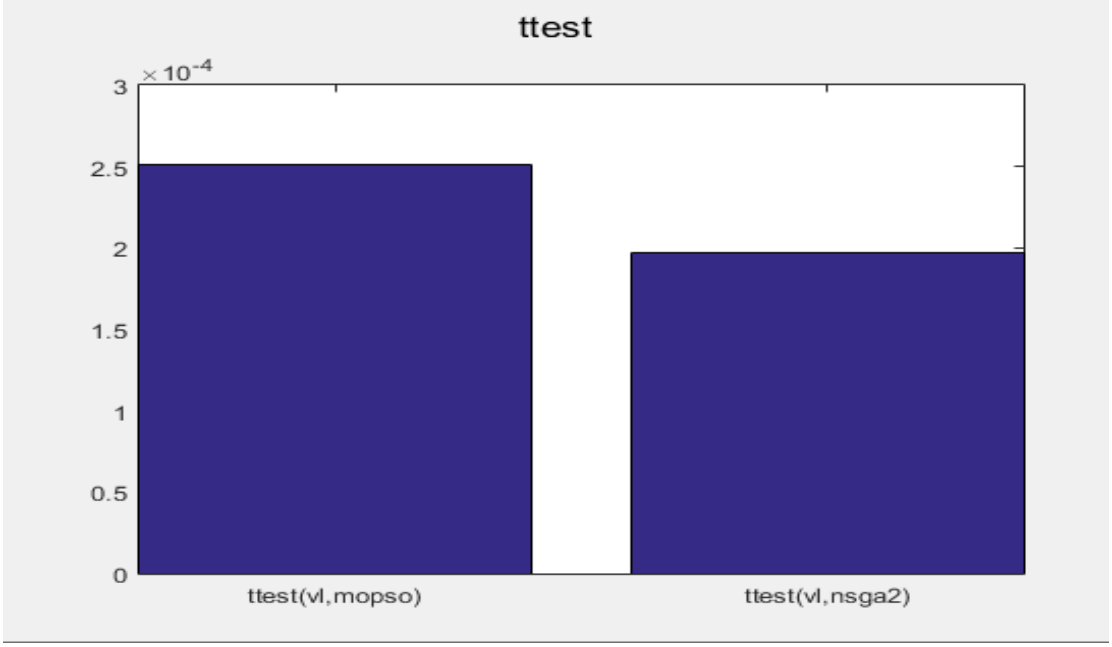
Search Space: [-10 10]

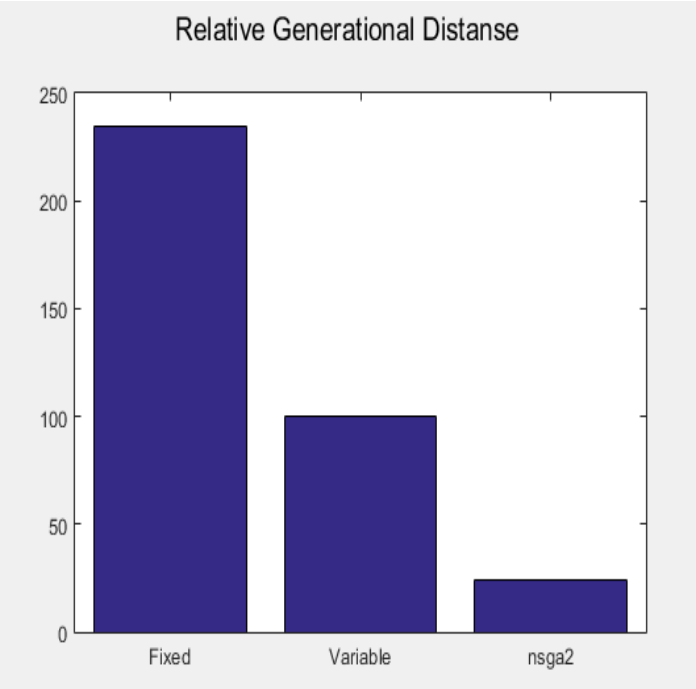
Lower Length: 1 population Size: 500 Iterations: 200
Higher Length: 30

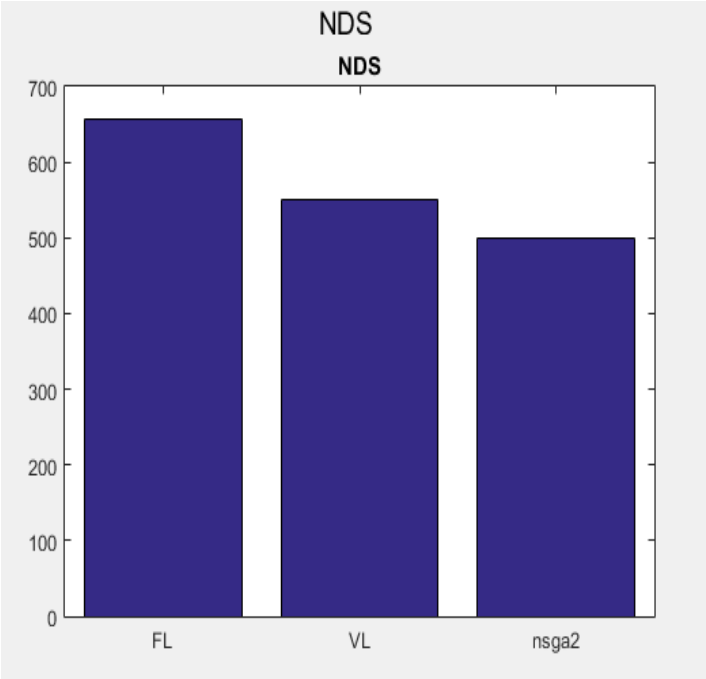
Results:

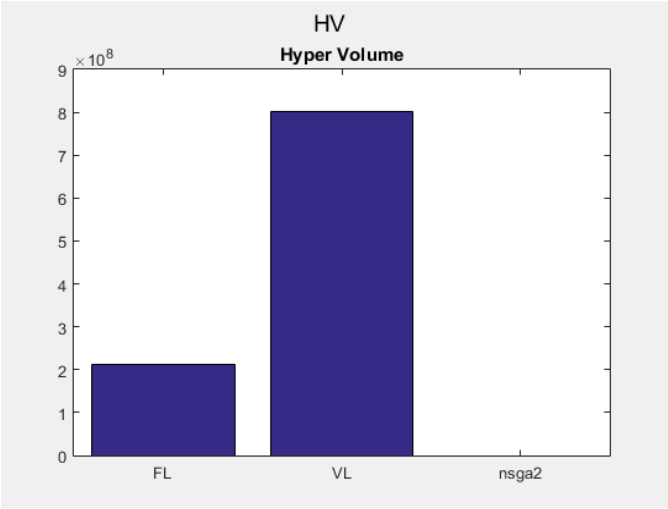


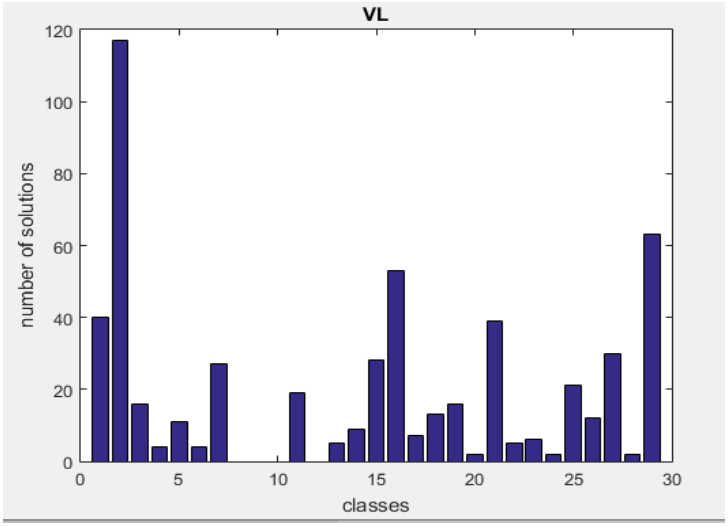


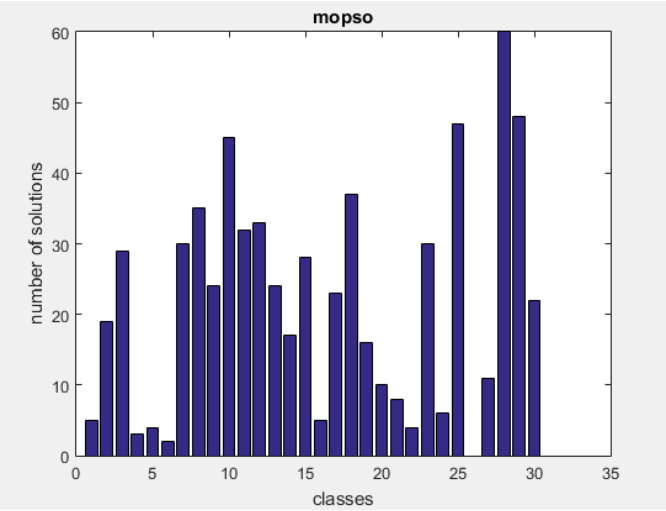


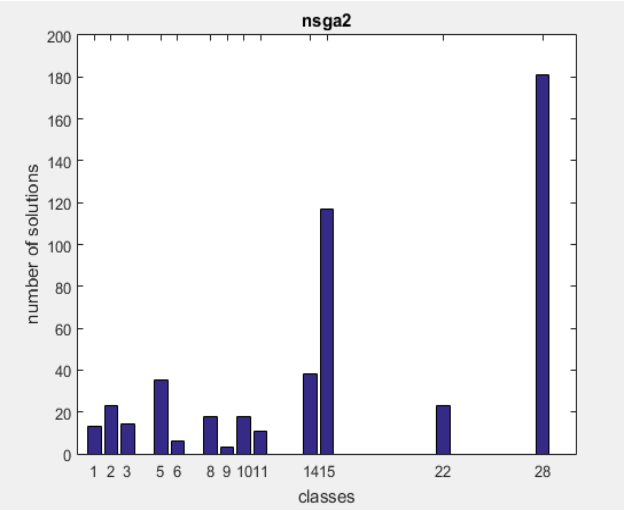

Relative Generational Distanse
250
200
150
100
50
0
Fixed
Variable
nsga2

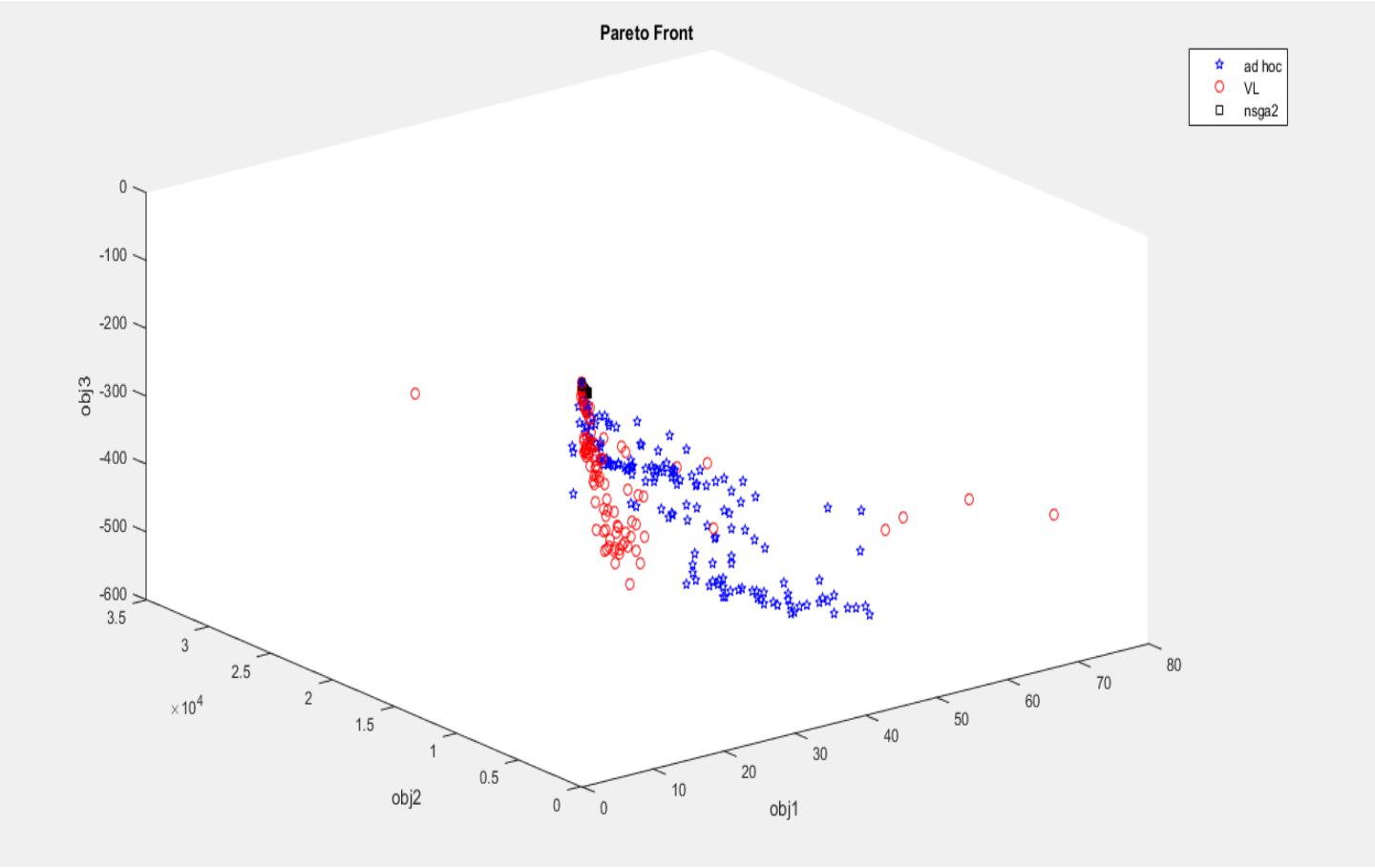

NDS
NDS
700
600
500
400
300
200
100
0
FL
VL
nsga2


HV
Hyper Volume
×10^8
9
8
7
6
5
4
3
2
1
0
FL
VL
nsga2


VL
number of solutions
120
100
80
60
40
20
0
0
5
10
15
20
25
30
classes


mopso
number of solutions
60
50
40
30
20
10
0
0
5
10
15
20
25
30
35
classes


nsga2
number of solutions
200
180
160
140
120
100
80
60
40
20
0
1 2 3
5 6
8 9 1011
1415
22
28
classes


Pareto Front
ad hoc
VL
nsga2
obj3
0
-100
-200
-300
-400
-500
-600
obj2
×10^4
3.5
3
2.5
2
1.5
1
0.5
0
obj1
0
10
20
30
40
50
60
70
80

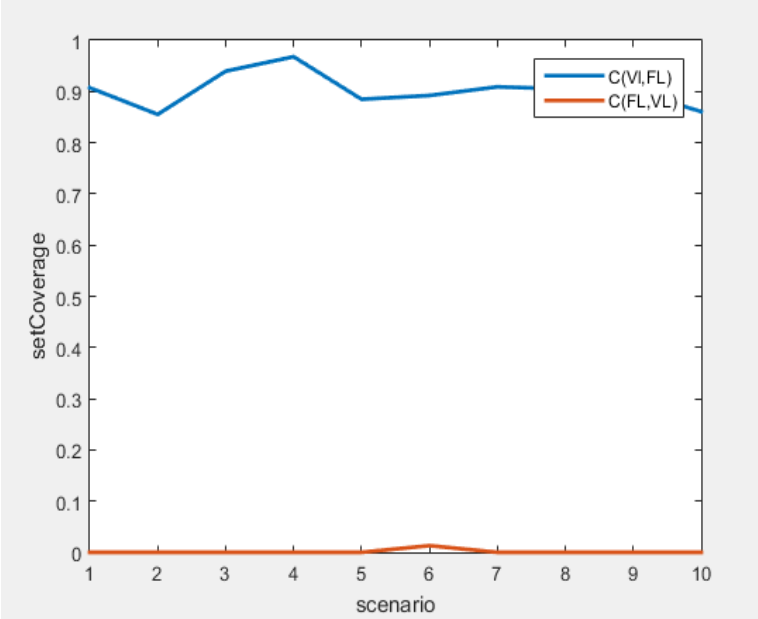
4- Rosen-Sphere

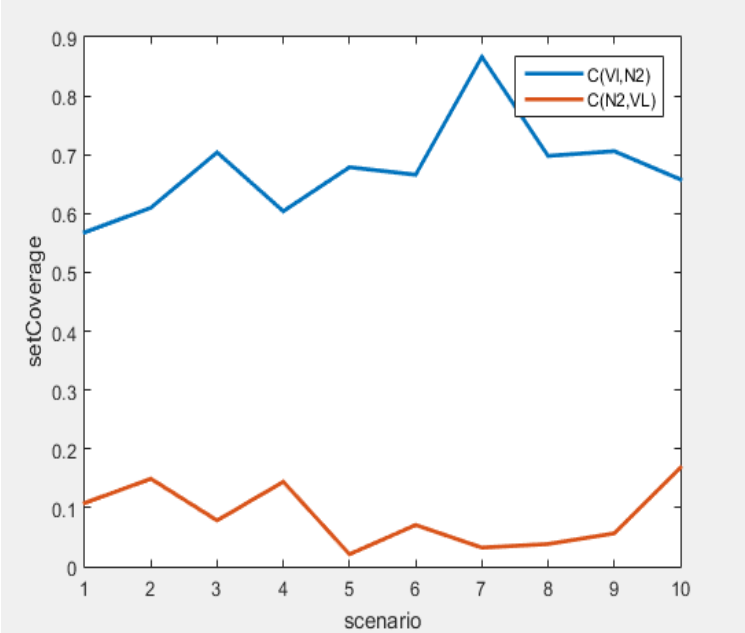
f(1)=RosenbrockObjFun(x);
f(2)=-sum(x.^2);

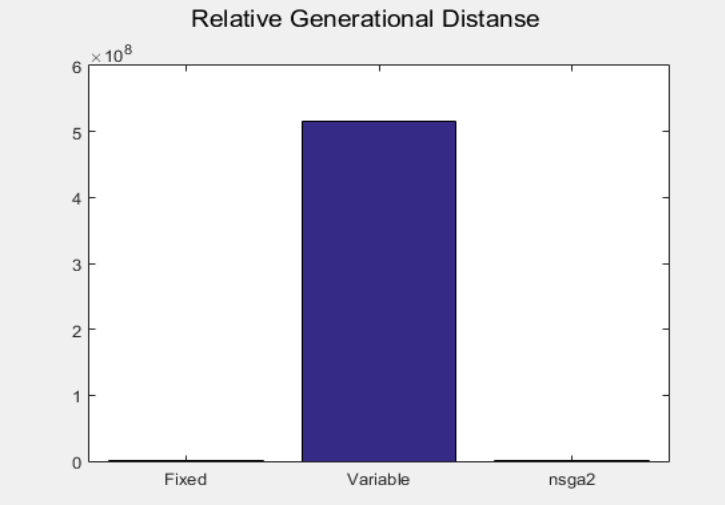
Search Space: [-10 10]

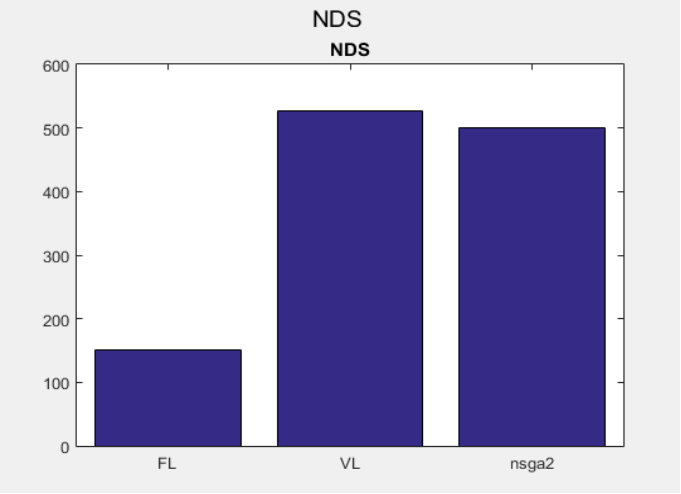
Lower Length: 1 population Size: 500 Iterations: 200
Higher Length: 30

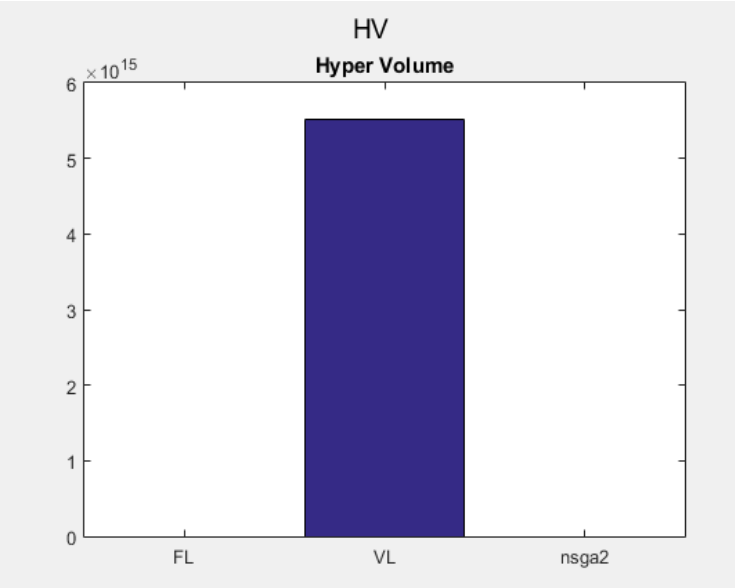
Results:

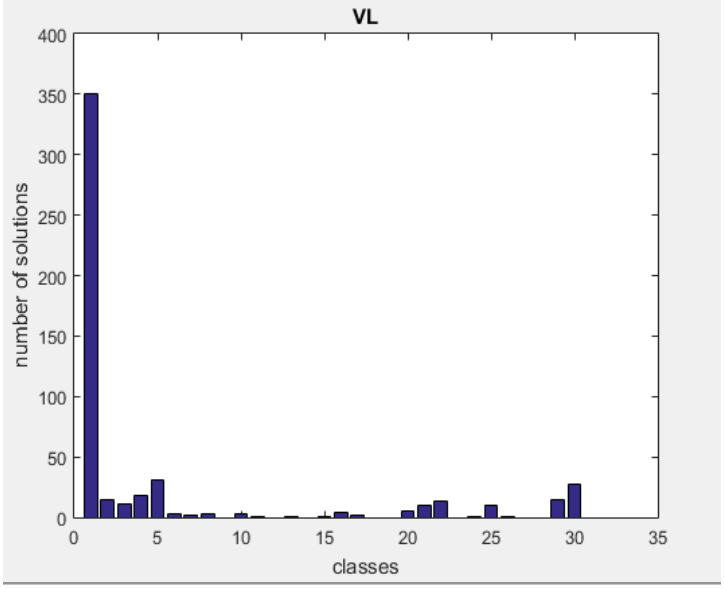


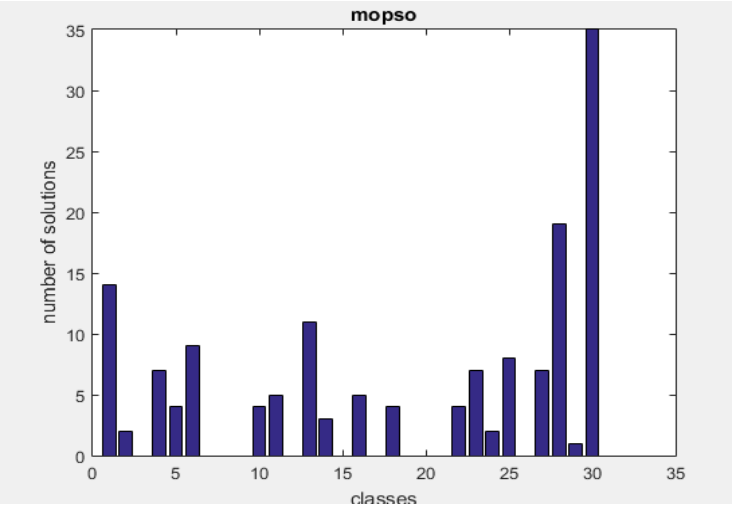


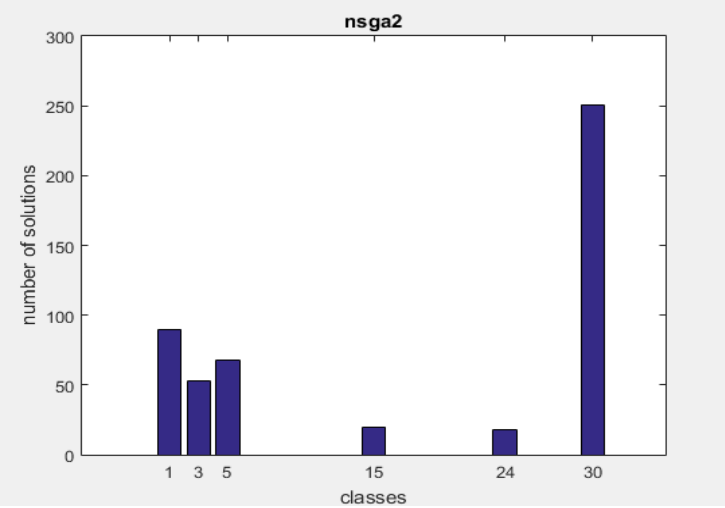


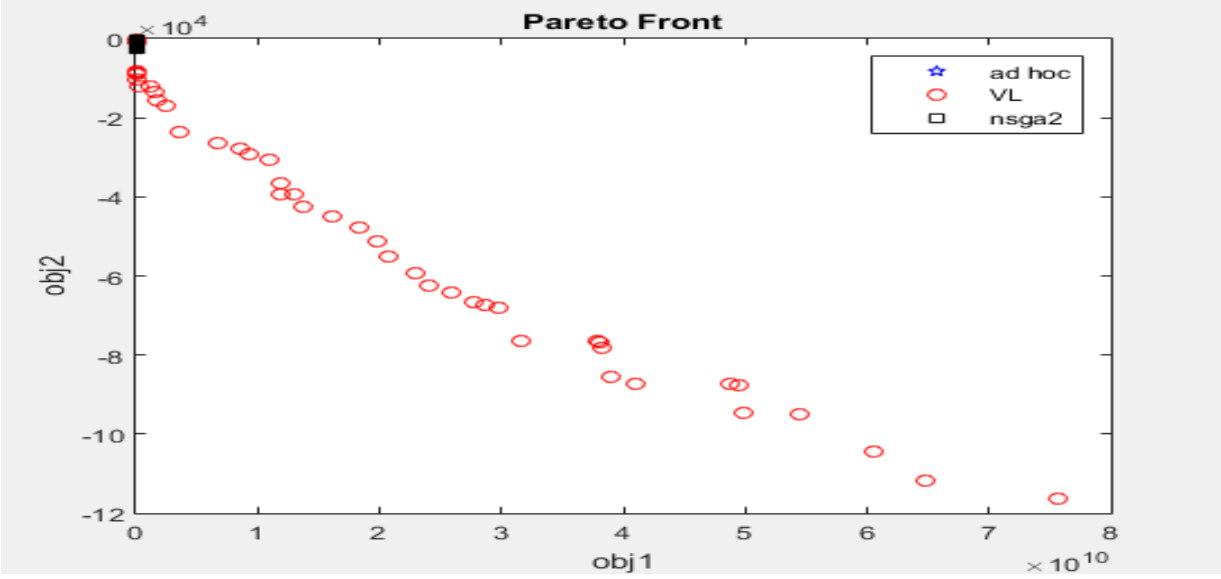



HV
Hyper Volume
×10^15
6
5
4
3
2
1
0
FL
VL
nsga2


VL
number of solutions
400
350
300
250
200
150
100
50
0
0
5
10
15
20
25
30
35
classes


mopso
number of solutions
35
30
25
20
15
10
5
0
0
5
10
15
20
25
30
35
classes


nsga2
number of solutions
300
250
200
150
100
50
0
1
3
5
15
24
30
classes

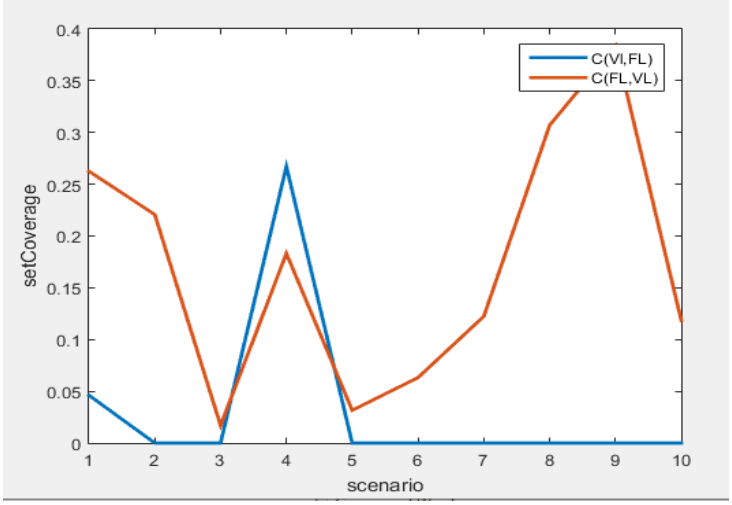

Pareto Front
×10^4
0
-2
-4
-6
-8
-10
-12
obj2
ad hoc
VL
nsga2
0
1
2
3
4
5
6
7
8
obj 1
×10^10

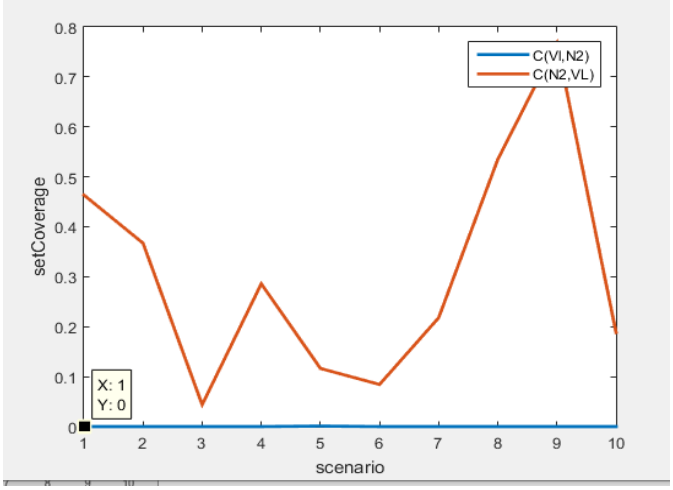
5- stybtang_Griewanks_Schwefel

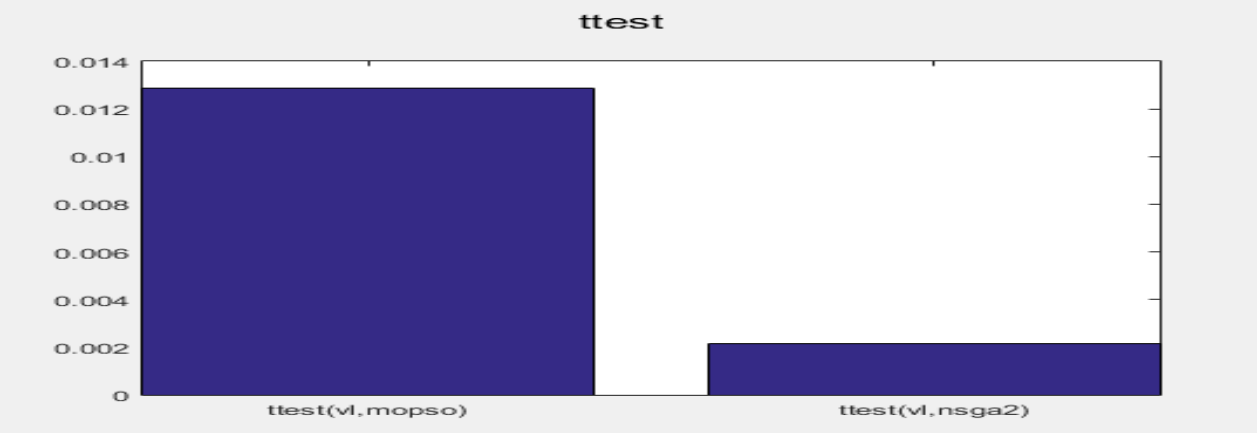
Objectives:
f(1)= stybtang(x);
f(2)= Griewanks(x);
f(3)= Schwefel(x);

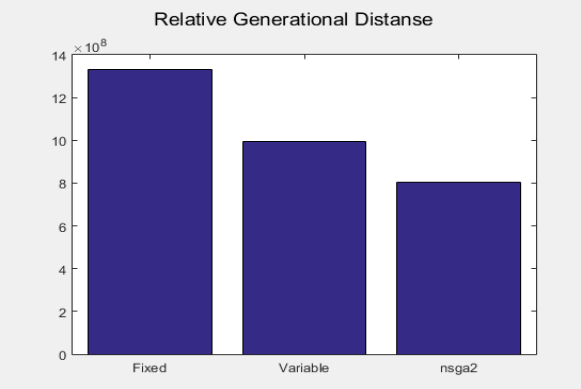
Search Space: [-600 600]

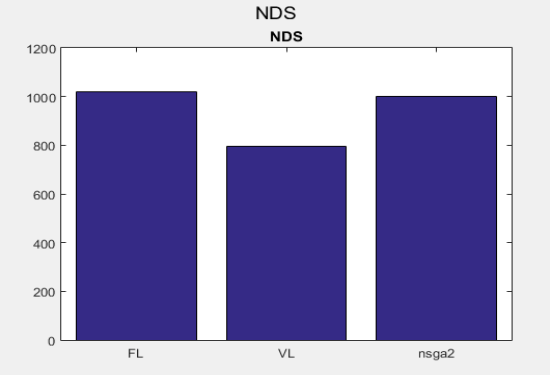
Lower Length: 1 population Size: 1000 Iterations: 200
Higher Length: 30

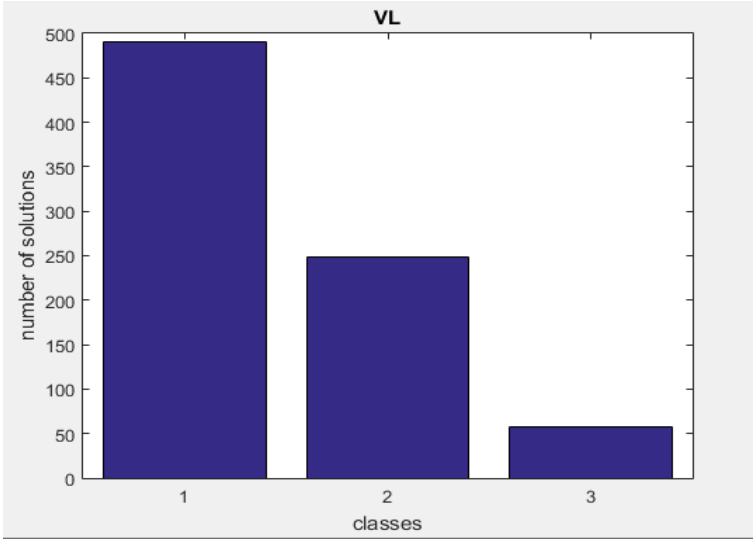


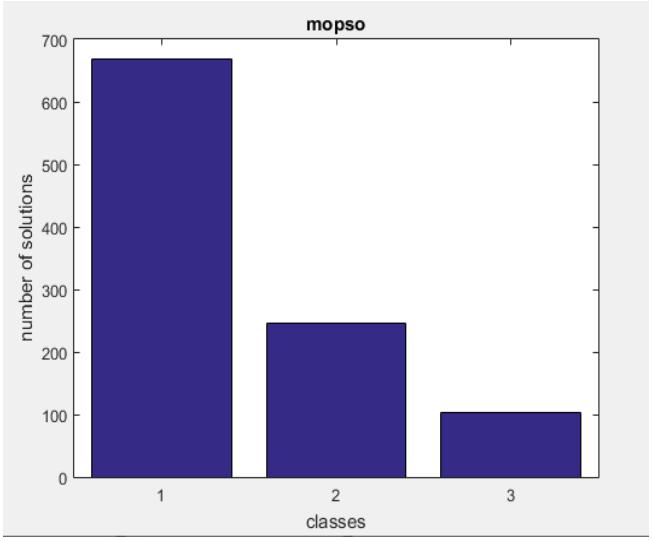


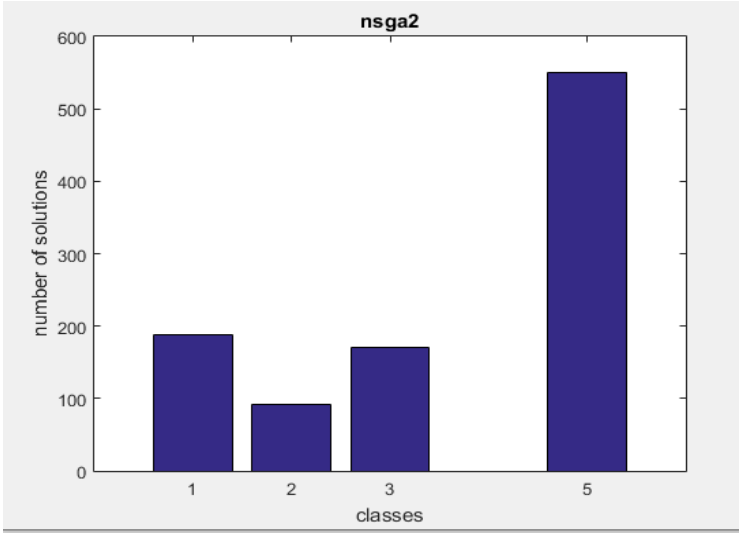


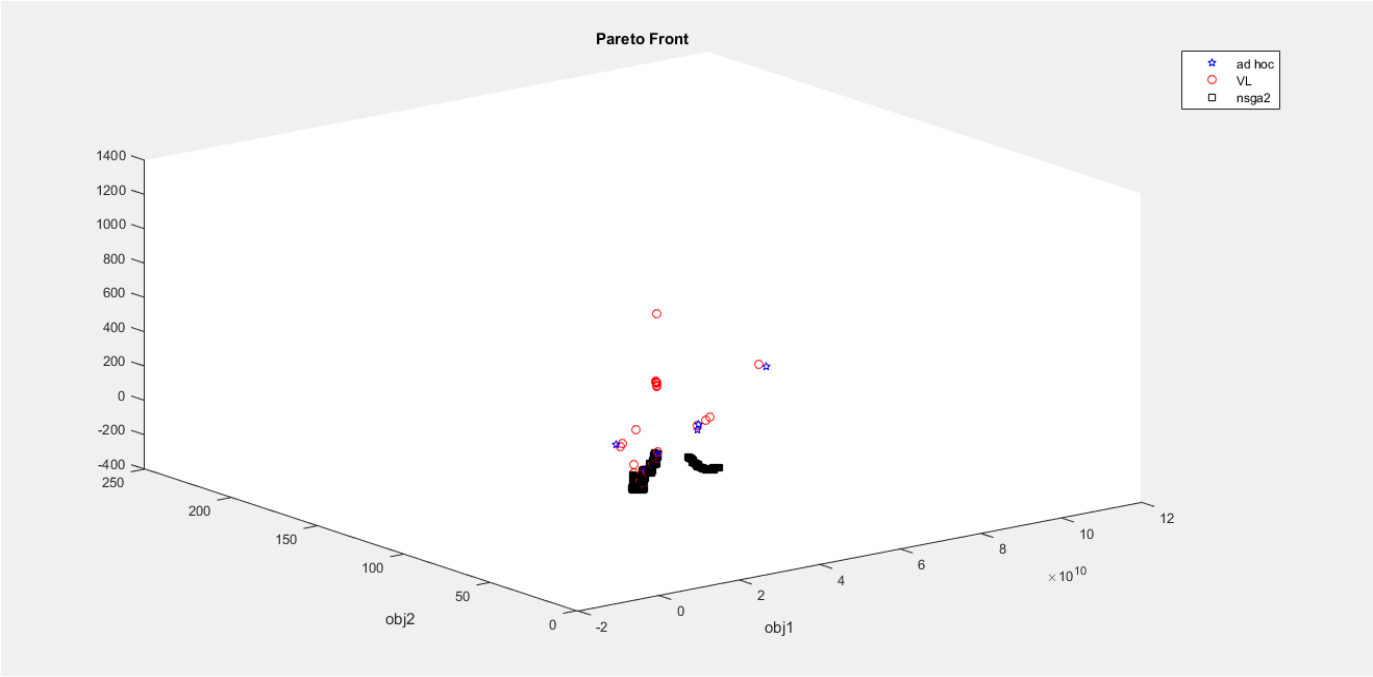





VL
number of solutions
classes
500
450
400
350
300
250
200
150
100
50
0
1
2
3


mopso
number of solutions
classes
700
600
500
400
300
200
100
0
1
2
3


nsga2
number of solutions
classes
600
500
400
300
200
100
0
1
2
3
5

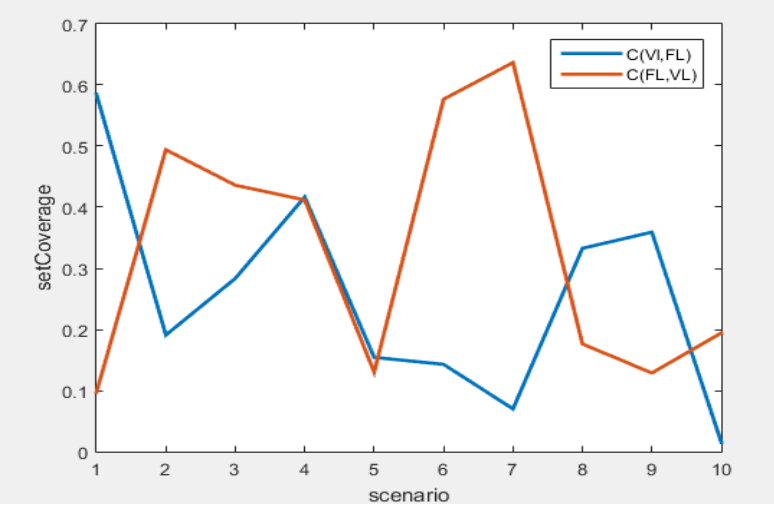

Pareto Front
ad hoc
VL
nsga2
1400
1200
1000
800
600
400
200
0
-200
-400
250
200
150
100
50
0
obj2
-2
0
2
4
6
8
10
12
×10^10
obj1

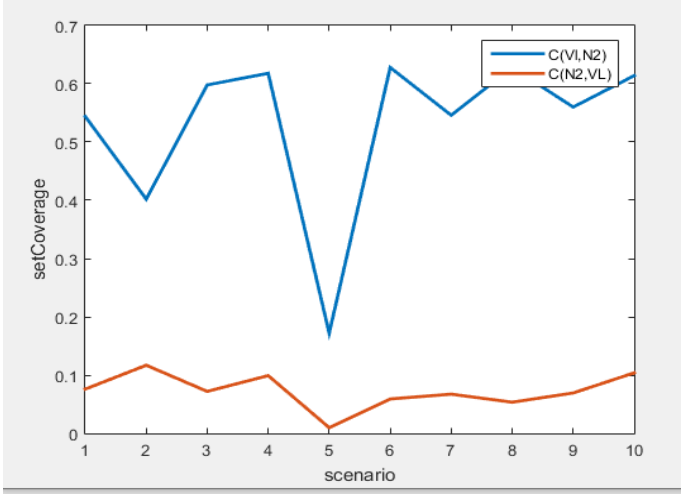
6- Rastrigin-stybtang

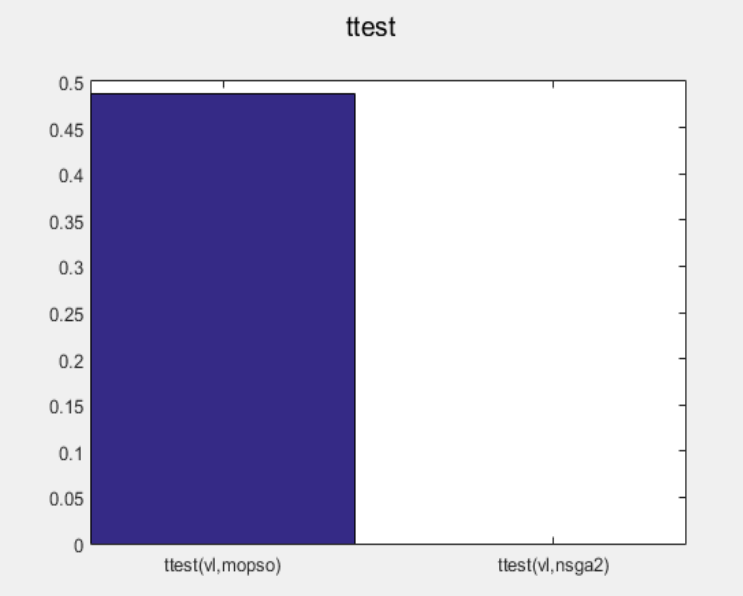
Objectives:
f(1)=Rastrigin(x);
f(2)=stybtang(x);

Search Space: [-5.12 5.12]

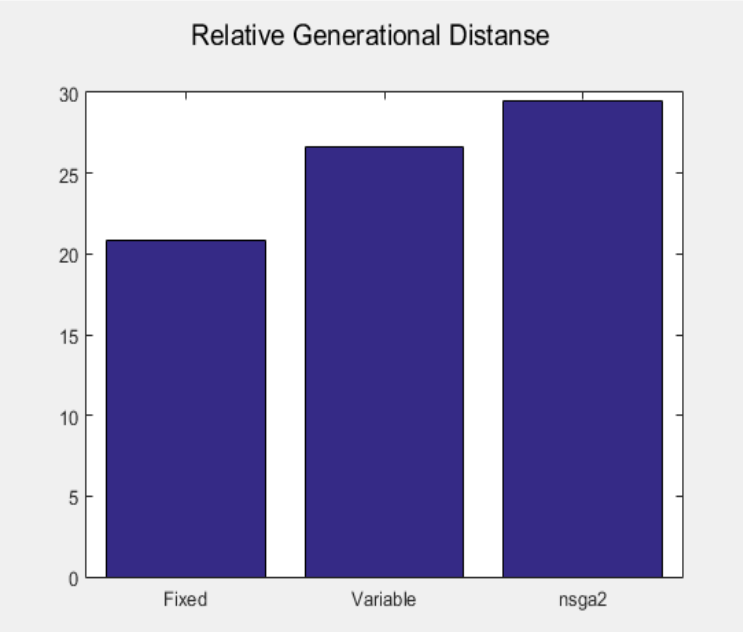
Lower Length: 1 population Size: 500 Iterations: 200
Higher Length: 30

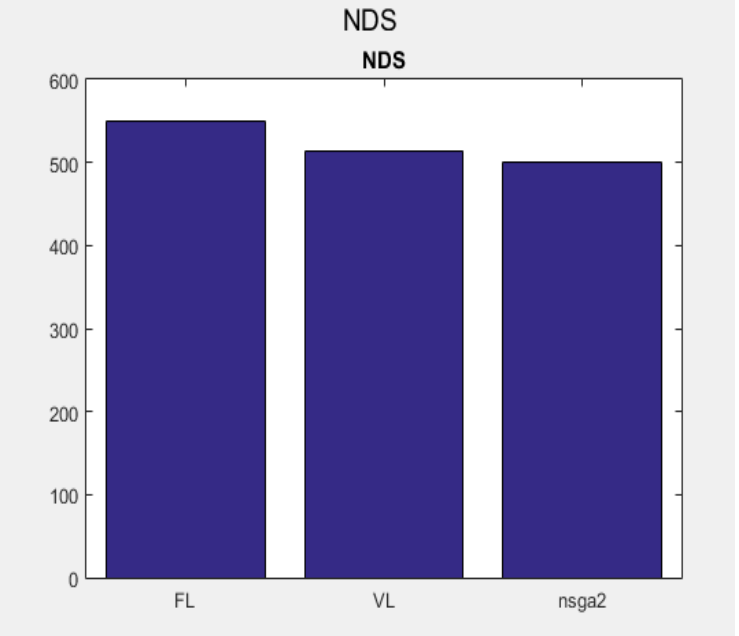


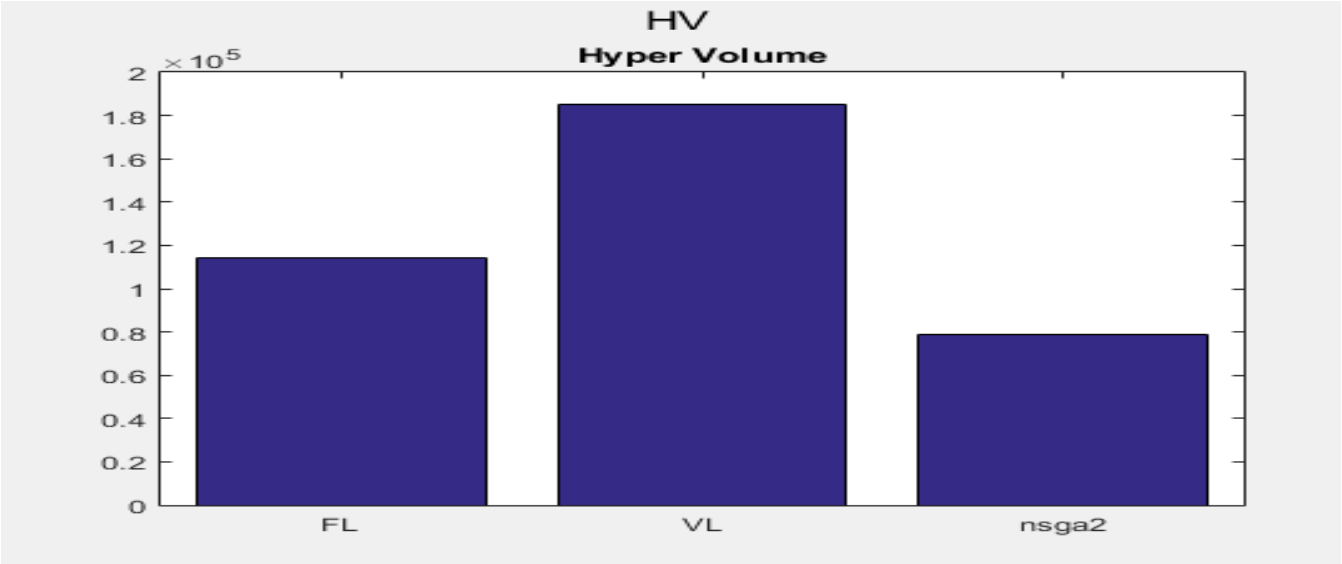


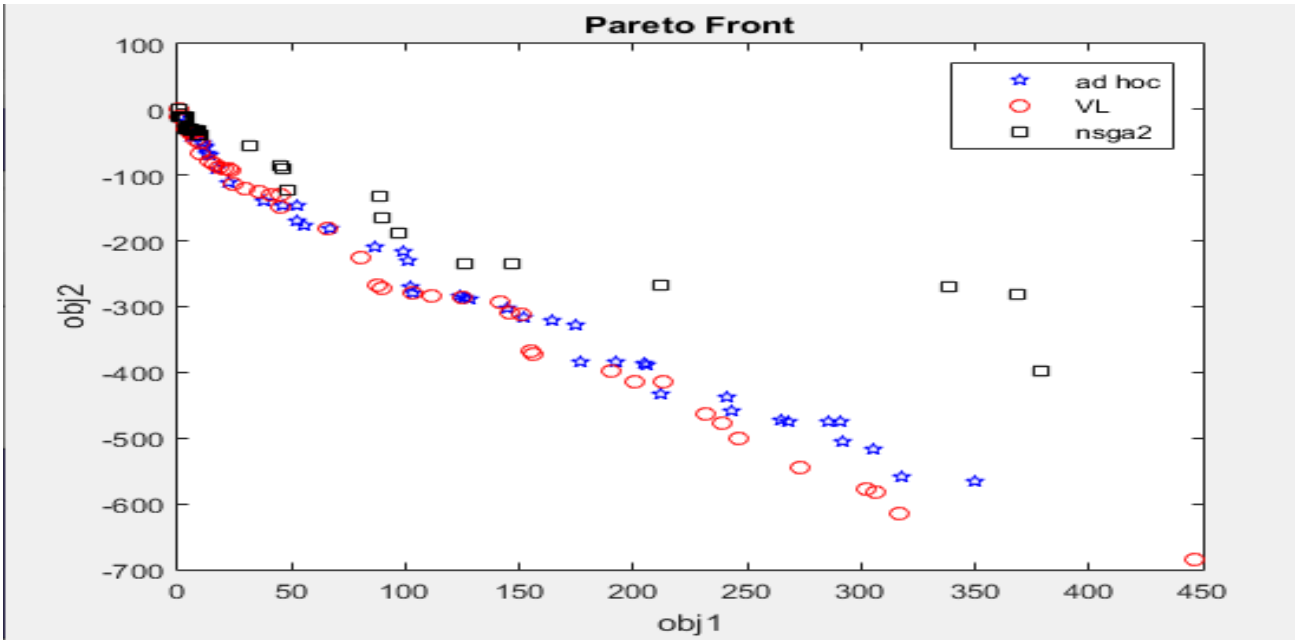


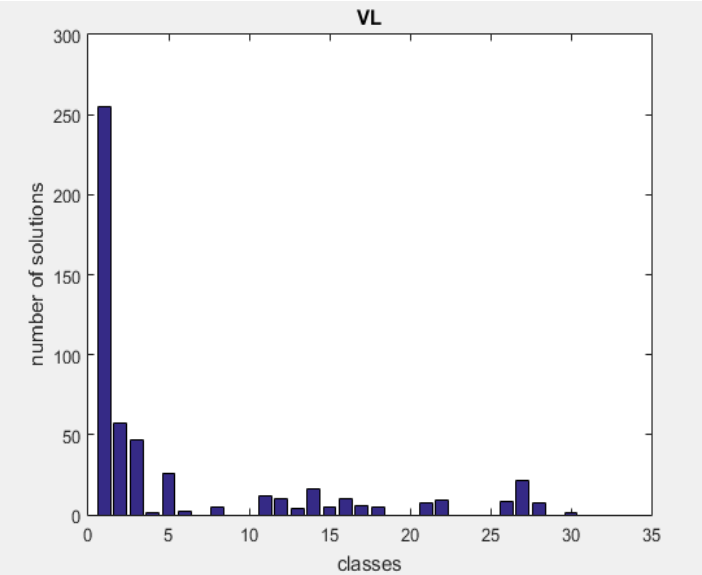
There is no significant difference vetween mopso and vlmopso

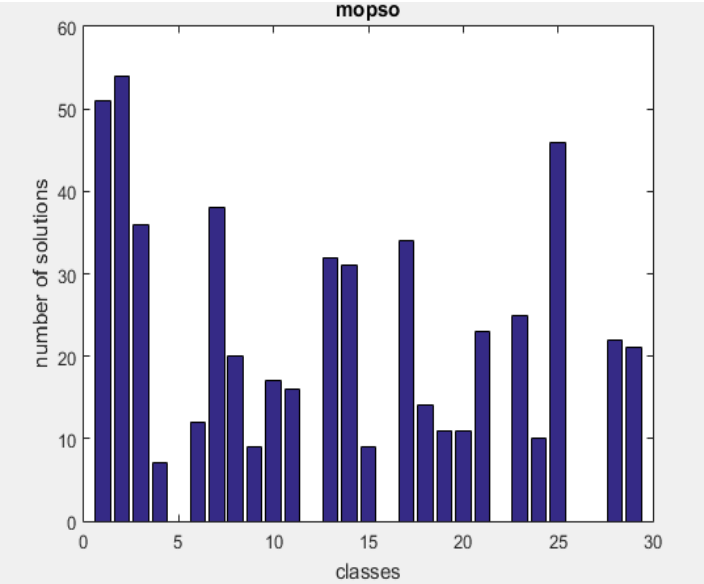

Relative Generational Distanse
30
25
20
15
10
5
0
Fixed
Variable
nsga2

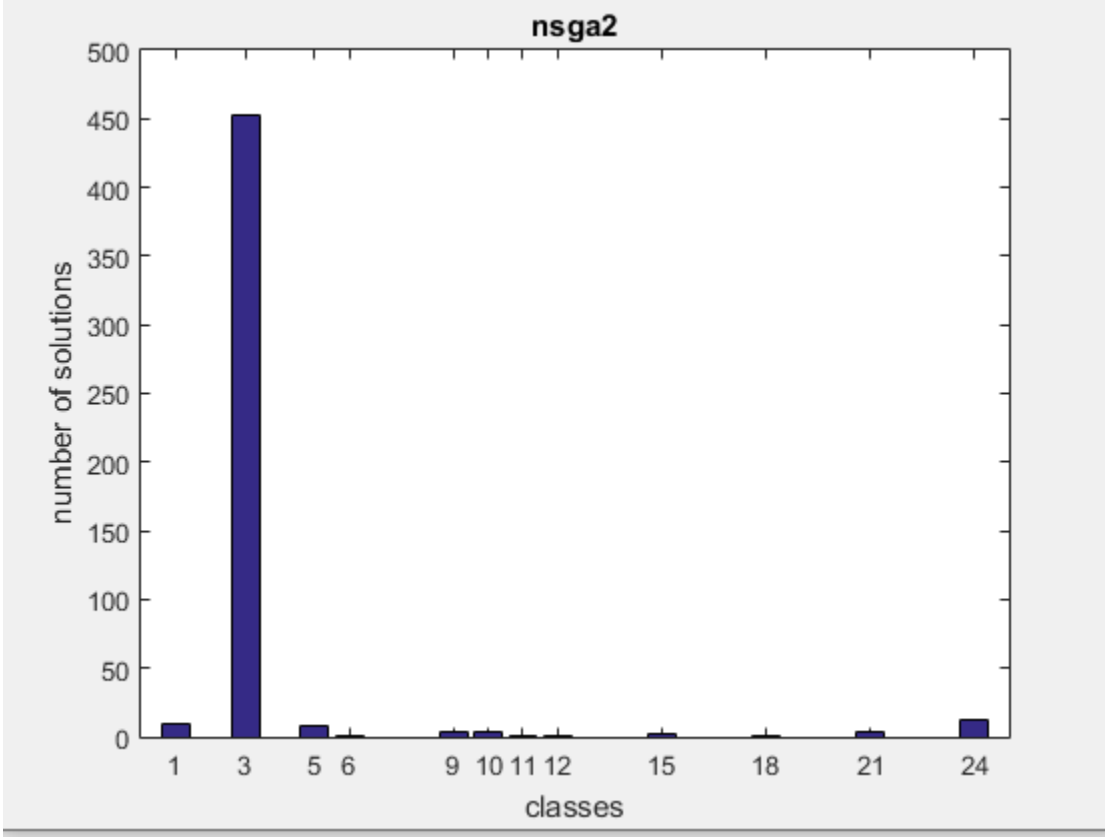

NDS
NDS
600
500
400
300
200
100
0
FL
VL
nsga2


HV
Hyper Volume
×10^5
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
FL
VL
nsga2


Pareto Front
ad hoc
VL
nsga2
obj2
obj1
100
0
-100
-200
-300
-400
-500
-600
-700
0
50
100
150
200
250
300
350
400
450


VL
number of solutions
classes
0
50
100
150
200
250
300
0
5
10
15
20
25
30
35


mopso
number of solutions
classes
0
10
20
30
40
50
60
0
5
10
15
20
25
30

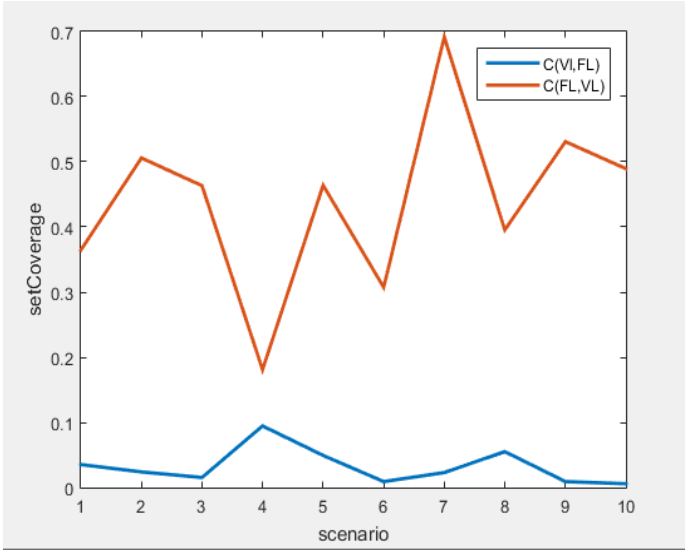

nsga2
number of solutions
classes
0
50
100
150
200
250
300
350
400
450
500
1
3
5
6
9
10
11
12
15
18
21
24

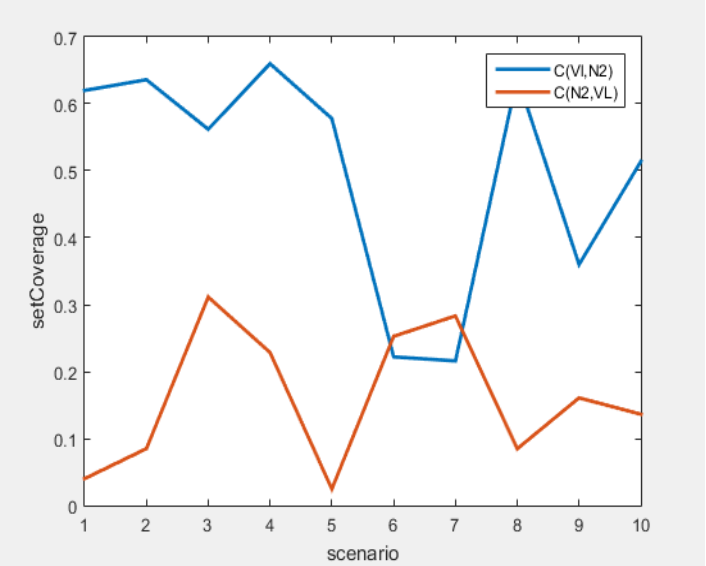
7- powell-stybtang-drastrigin

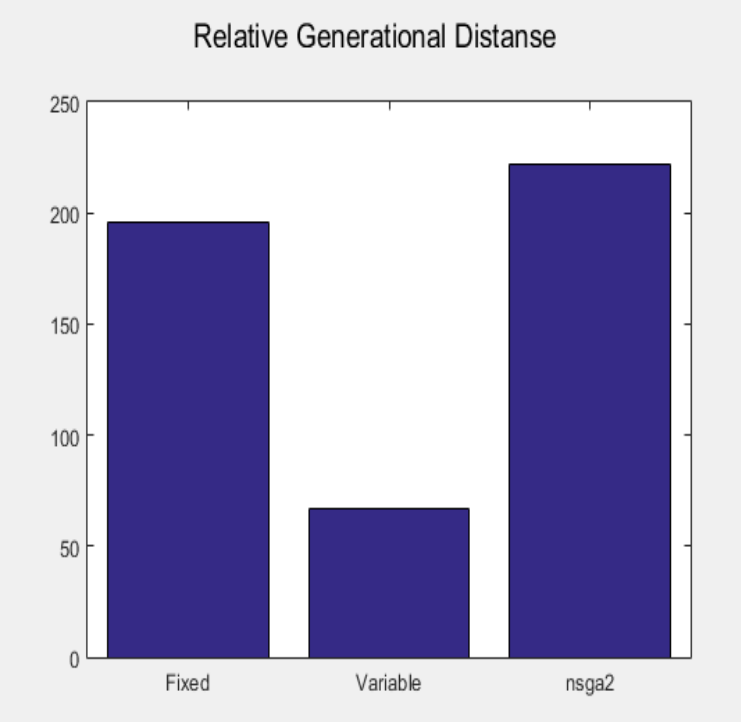
Objectives:
f(1)=powell(x);
f(2)=stybtang(x);
f(3)=DRastrigin(x);

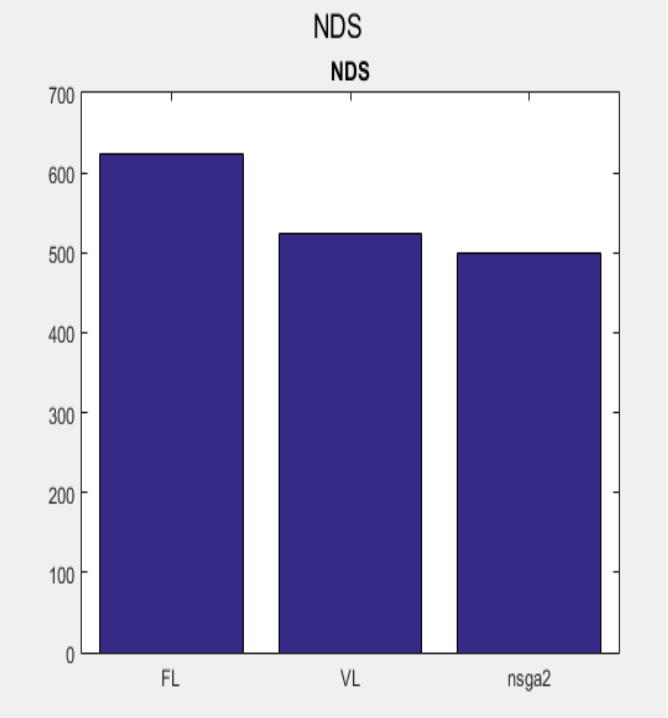
Search Space: [-5.12 5.12]

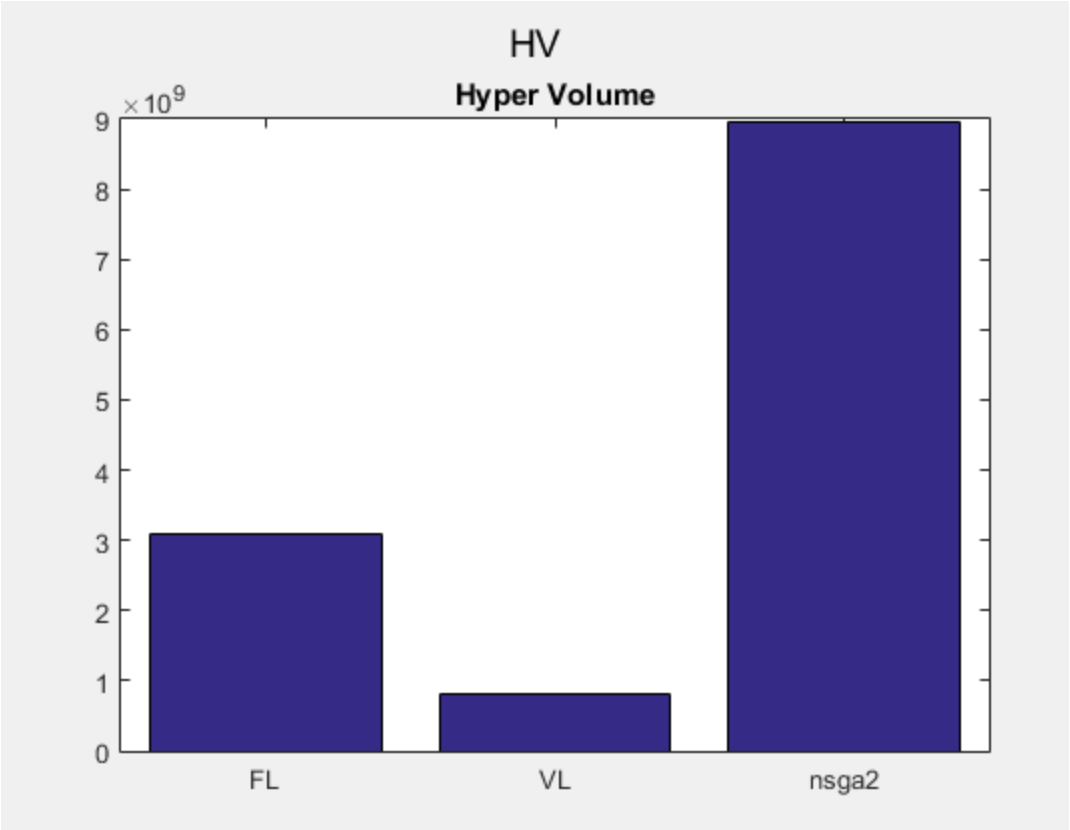
Lower Length: 1 population Size: 500 Iterations: 200
Higher Length: 30

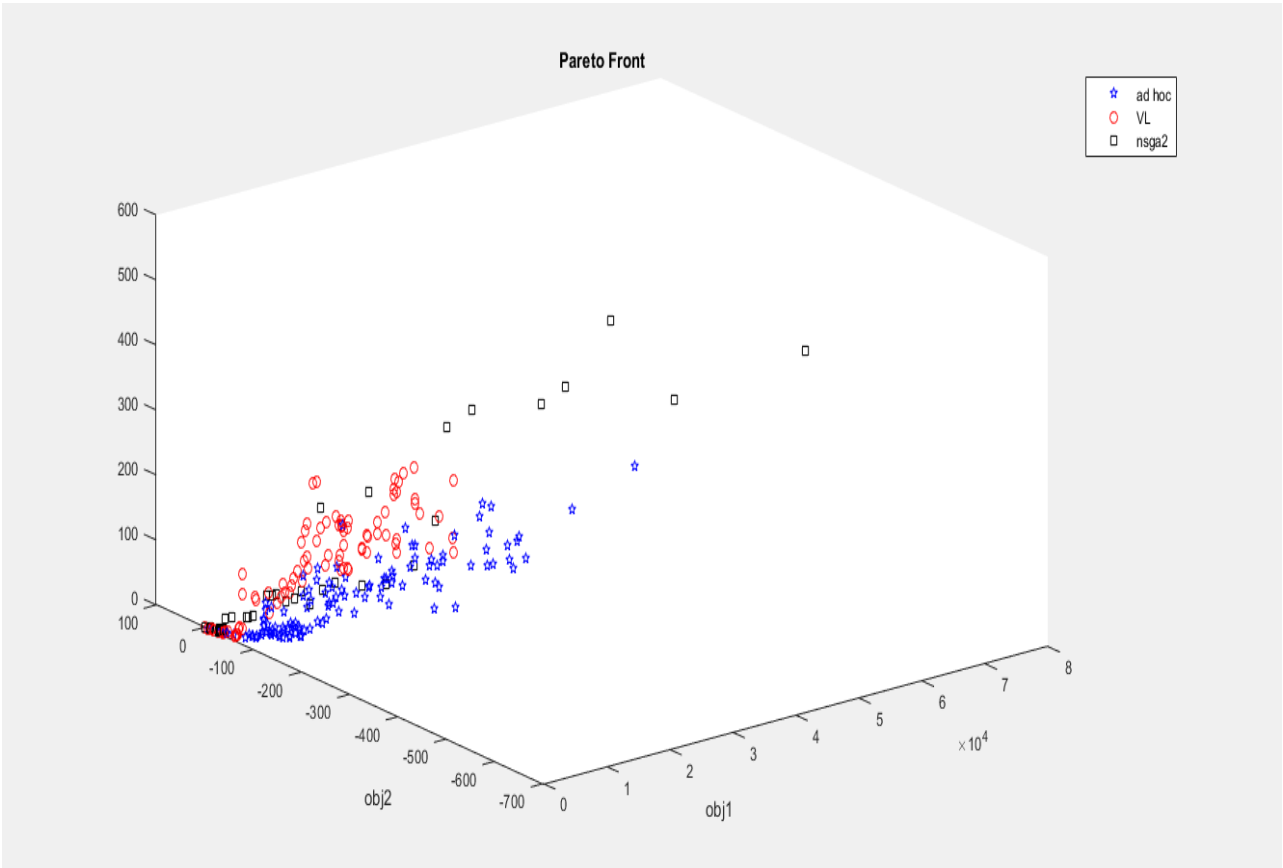


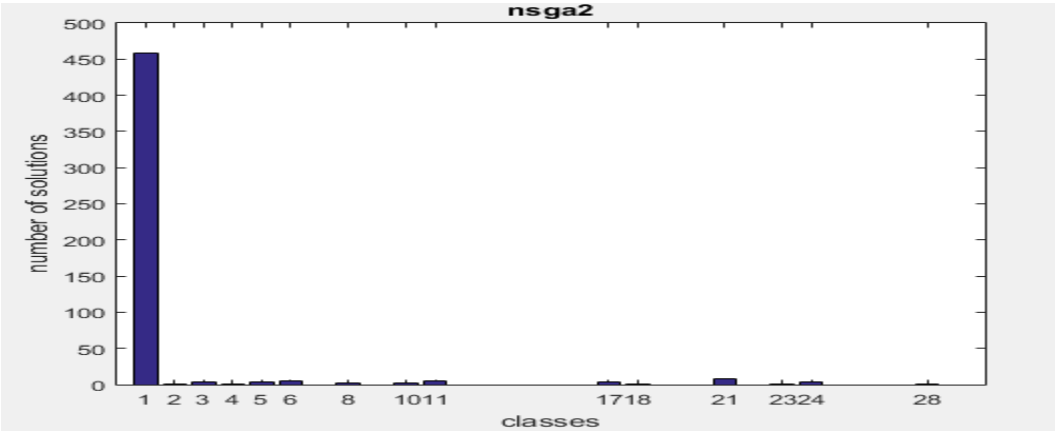


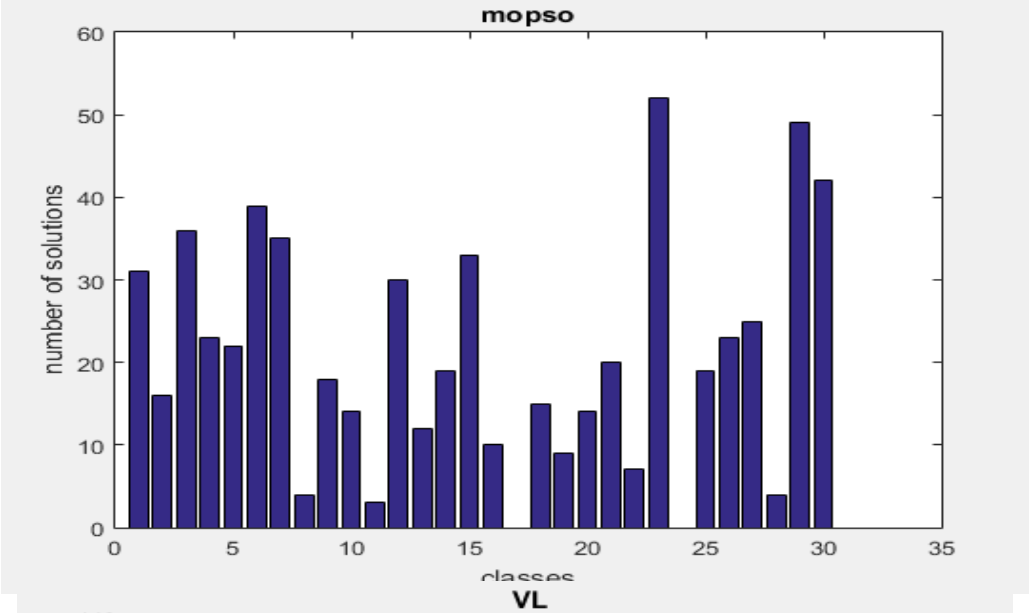

Relative Generational Distanse
250
200
150
100
50
0
Fixed
Variable
nsga2

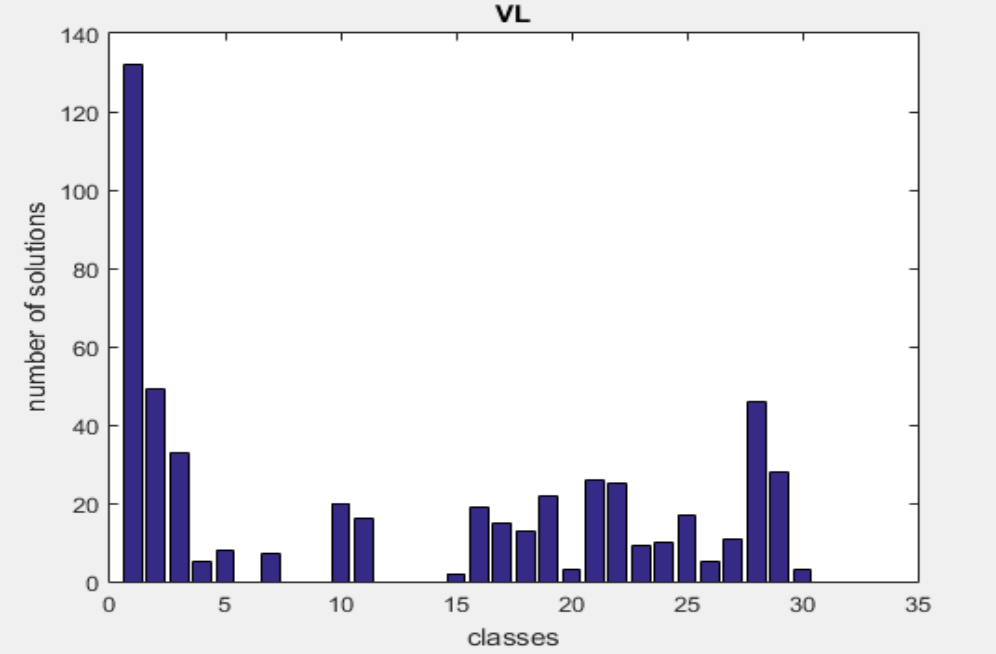

NDS
NDS
700
600
500
400
300
200
100
0
FL
VL
nsga2


HV
Hyper Volume
×10^9
9
8
7
6
5
4
3
2
1
0
FL
VL
nsga2


Pareto Front
ad hoc
VL
nsga2
600
500
400
300
200
100
0
100
0
-100
-200
-300
-400
-500
-600
-700
obj2
0
1
2
3
4
5
6
7
8
×10^4
obj1


nsga2
number of solutions
classes
1 2 3 4 5 6 8 1011 1718 21 2324 28


mopso
number of solutions

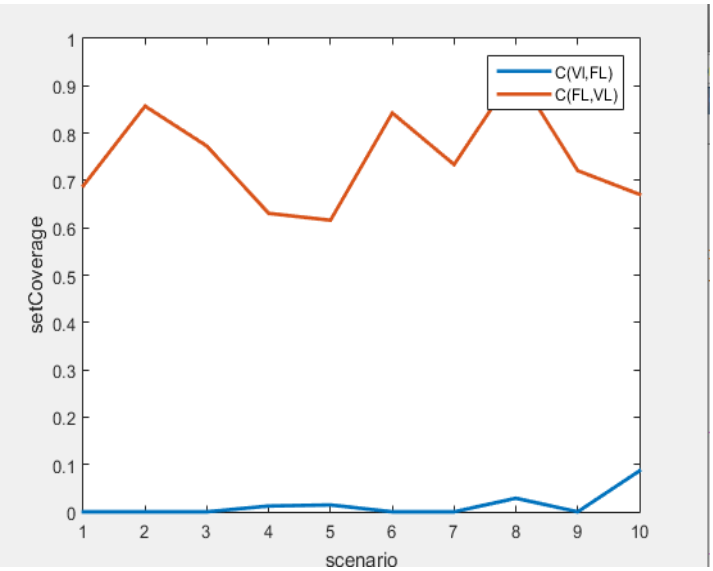

VL
number of solutions
classes

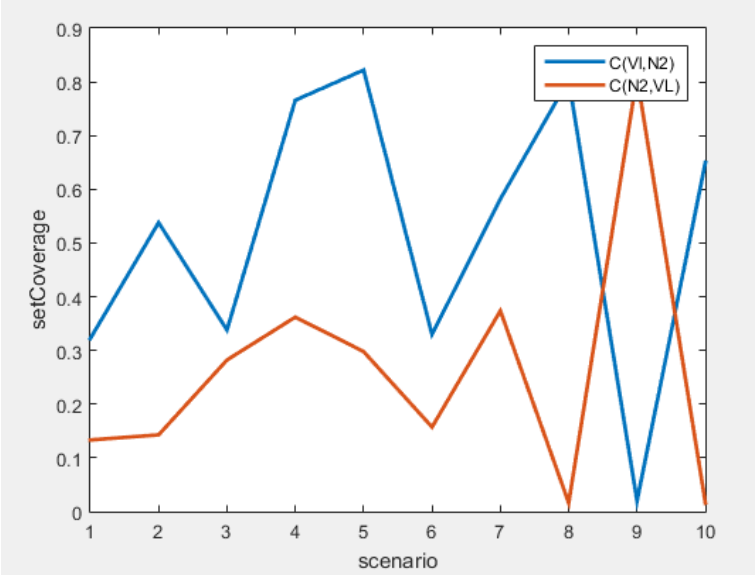
8- Weierstrass-stybtang

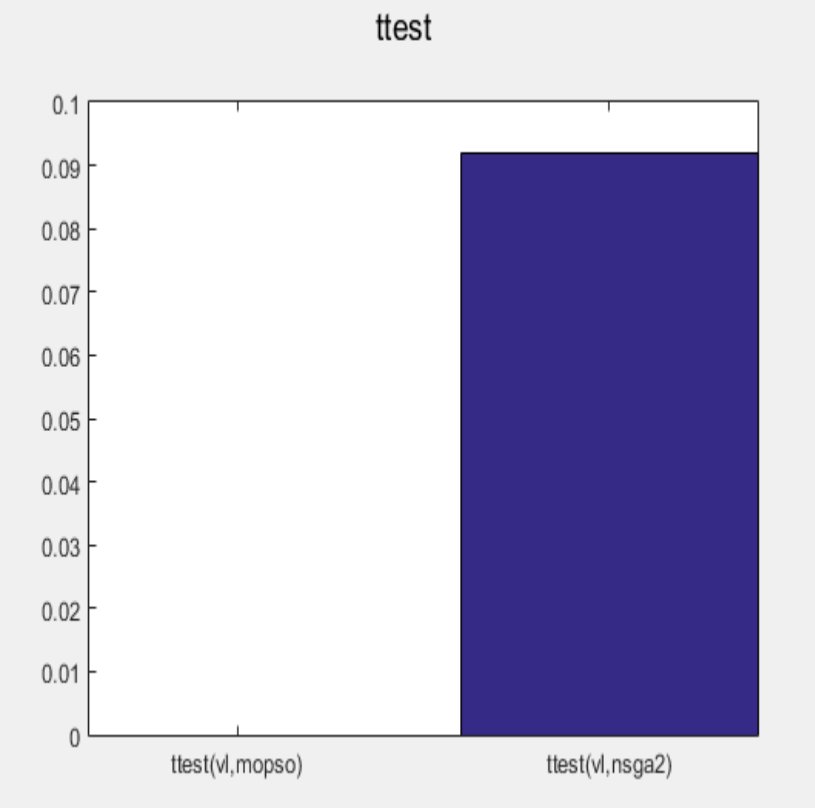
Objectives:
f(1)=Weierstrass(x);
f(2)=stybtang(x);

Search Space: [-5 5]

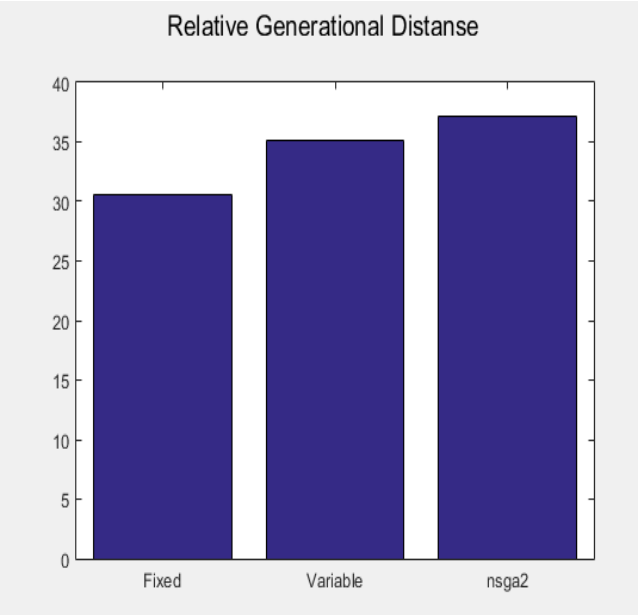
Lower Length: 1 population Size: 500 Iterations: 200
Higher Length: 30

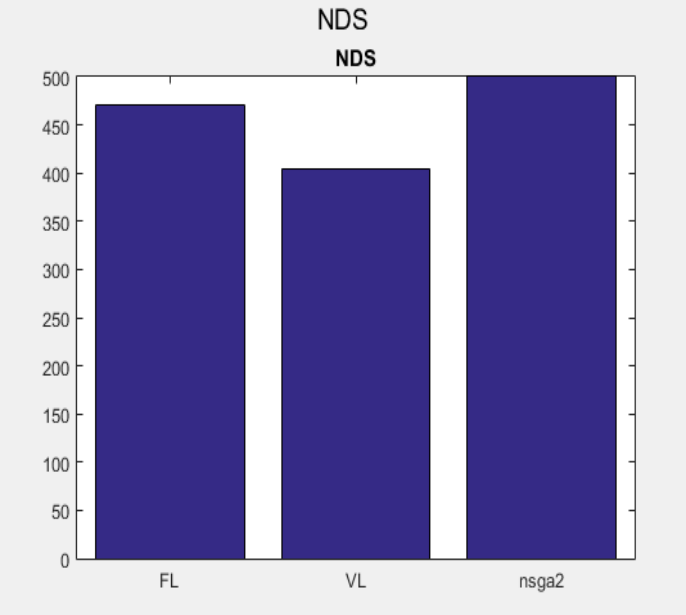


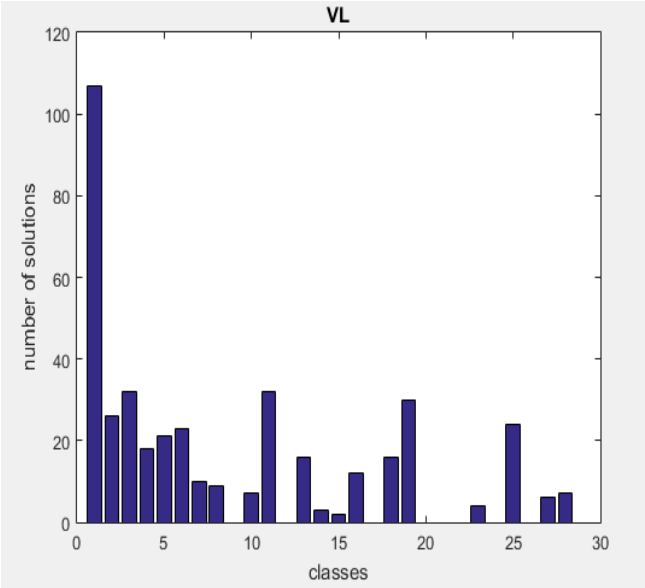


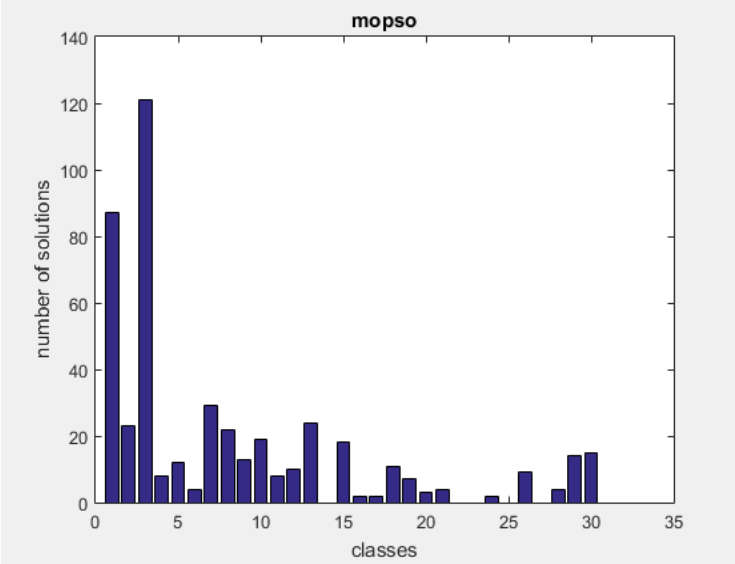


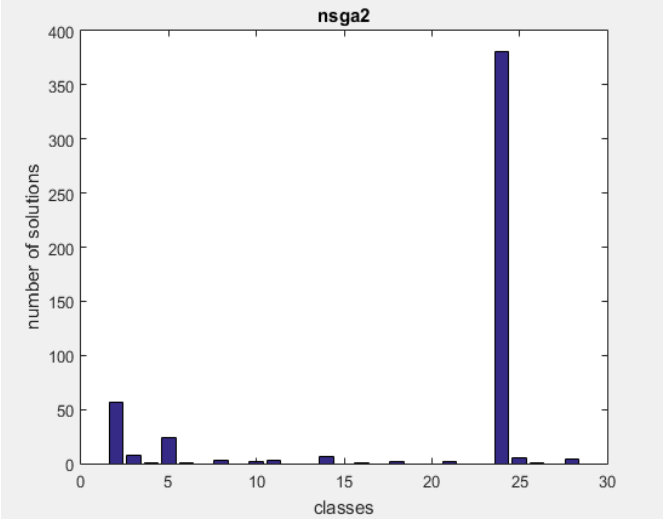
There is no significant difference between vlmopso and nsga2

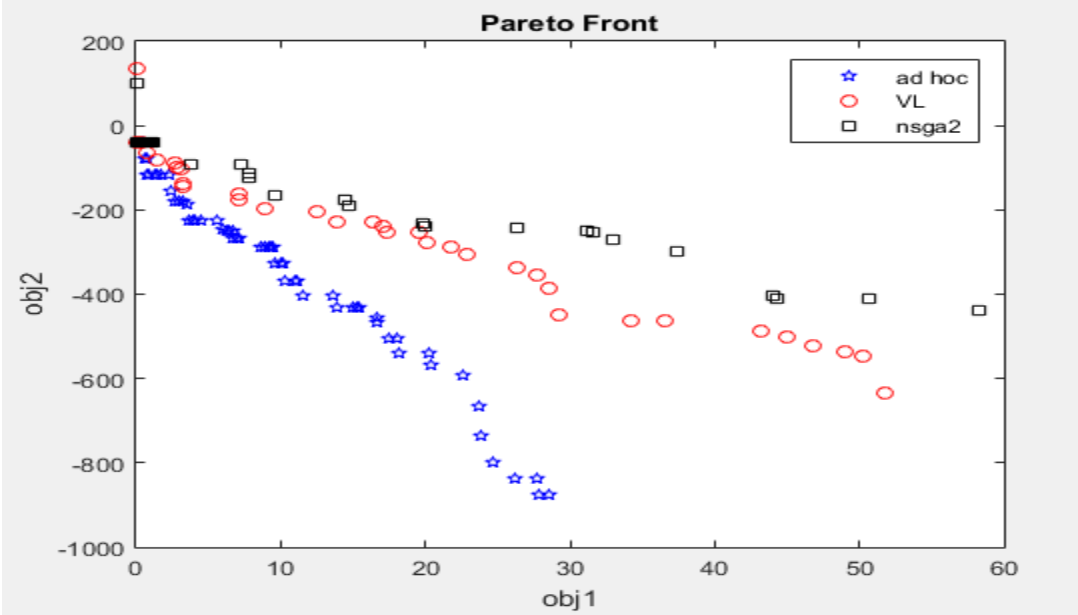

Relative Generational Distanse
40
35
30
25
20
15
10
5
0
Fixed
Variable
nsga2

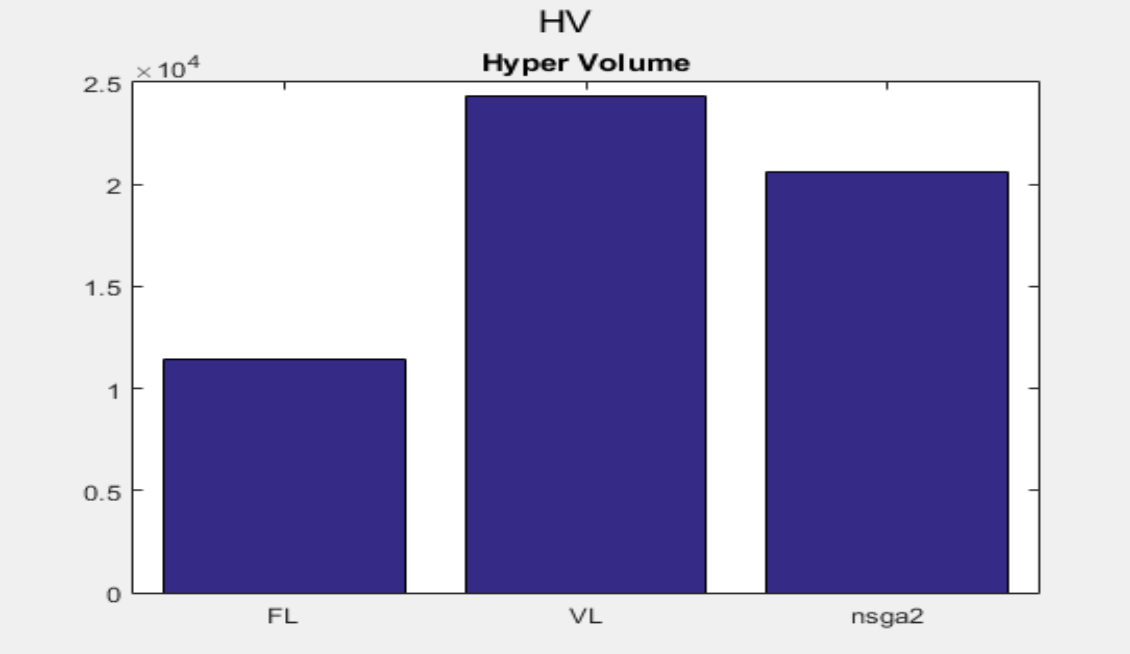

NDS
NDS
500
450
400
350
300
250
200
150
100
50
0
FL
VL
nsga2


VL
number of solutions
120
100
80
60
40
20
0
0
5
10
15
20
25
30
classes


mopso
number of solutions
140
120
100
80
60
40
20
0
0
5
10
15
20
25
30
35
classes


nsga2
number of solutions
400
350
300
250
200
150
100
50
0
0
5
10
15
20
25
30
classes


Pareto Front
ad hoc
VL
nsga2
obj2
obj1
200
0
-200
-400
-600
-800
-1000
0
10
20
30
40
50
60

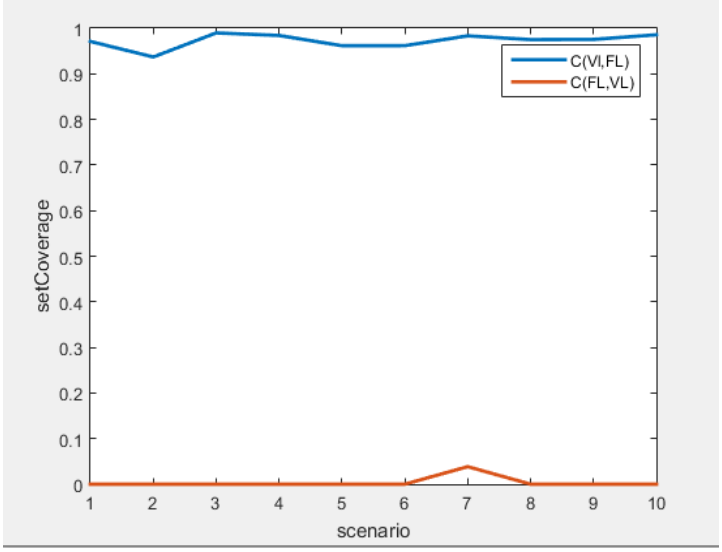

HV
Hyper Volume
×10^4
2.5
2
1.5
1
0.5
0
FL
VL
nsga2

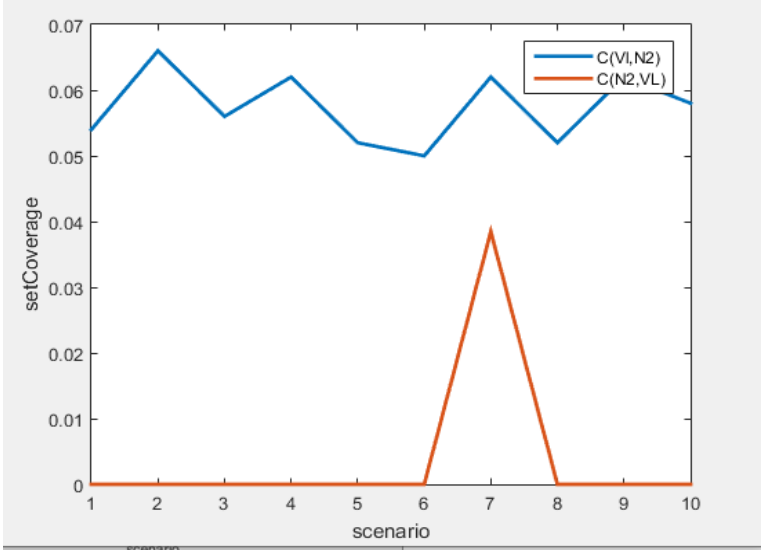
9- Rosen-Levy

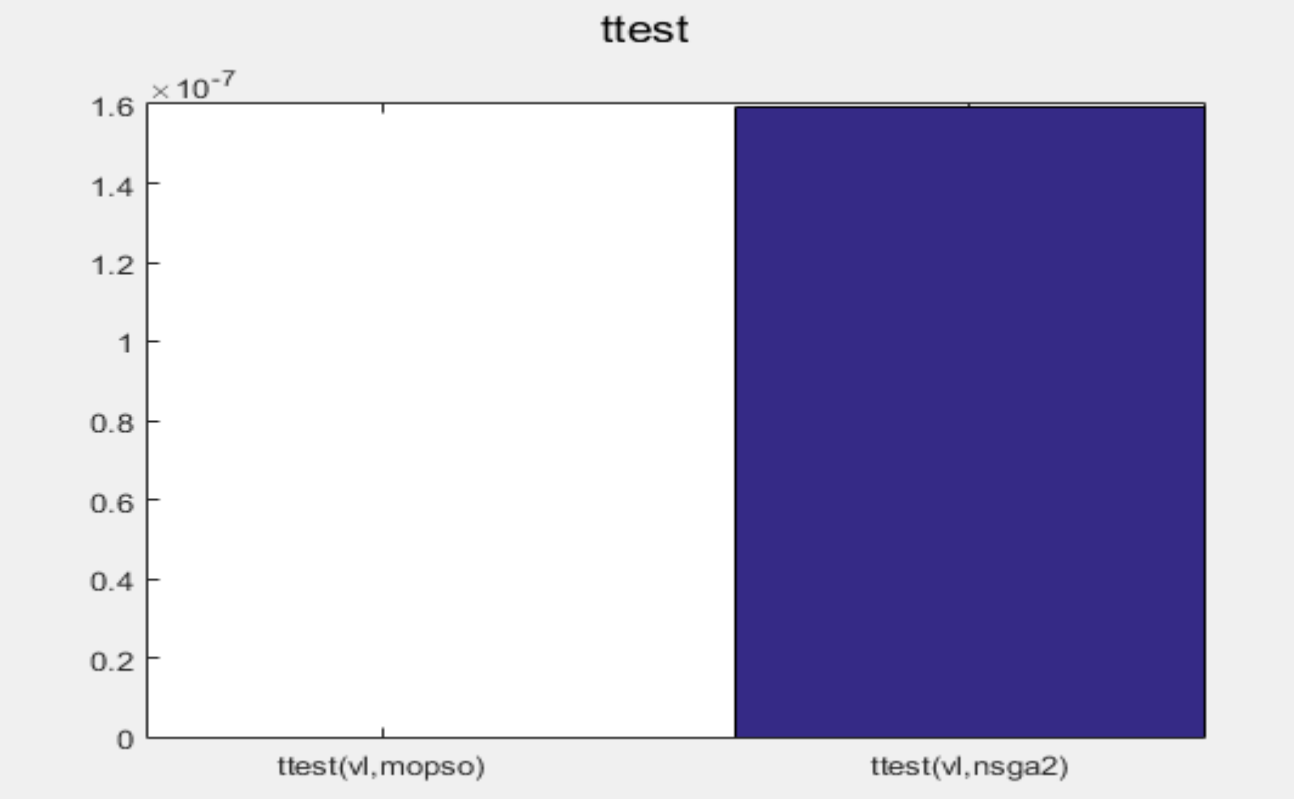
Objectives:
f(1)=RosenbrockObjFun(x);
f(2)=-levy(x);

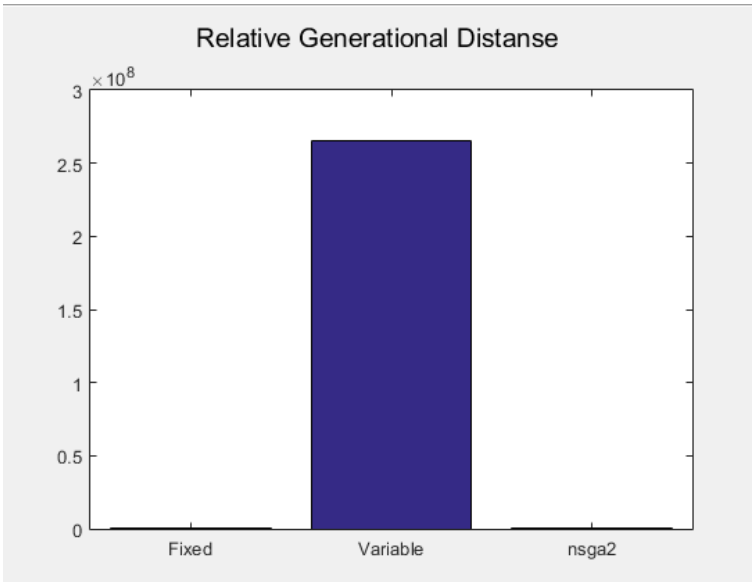
Search Space: [-10 10]

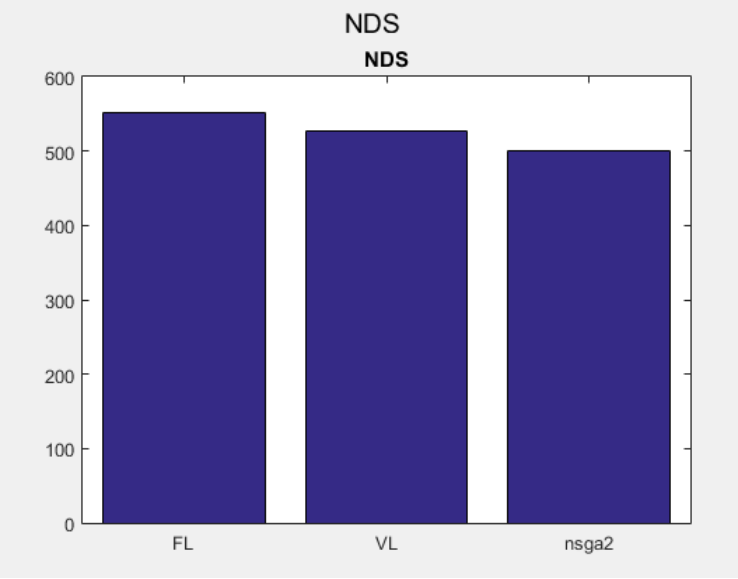
Lower Length: 1 population Size: 500 Iterations: 200
Higher Length: 30

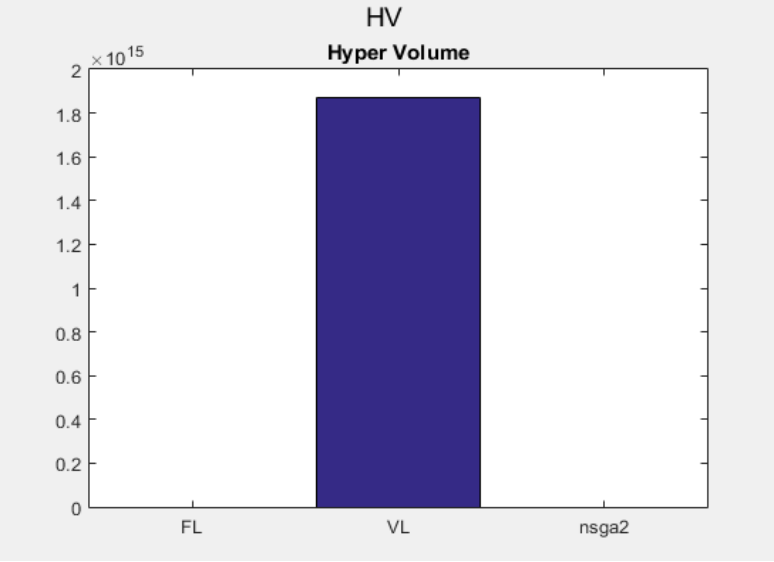


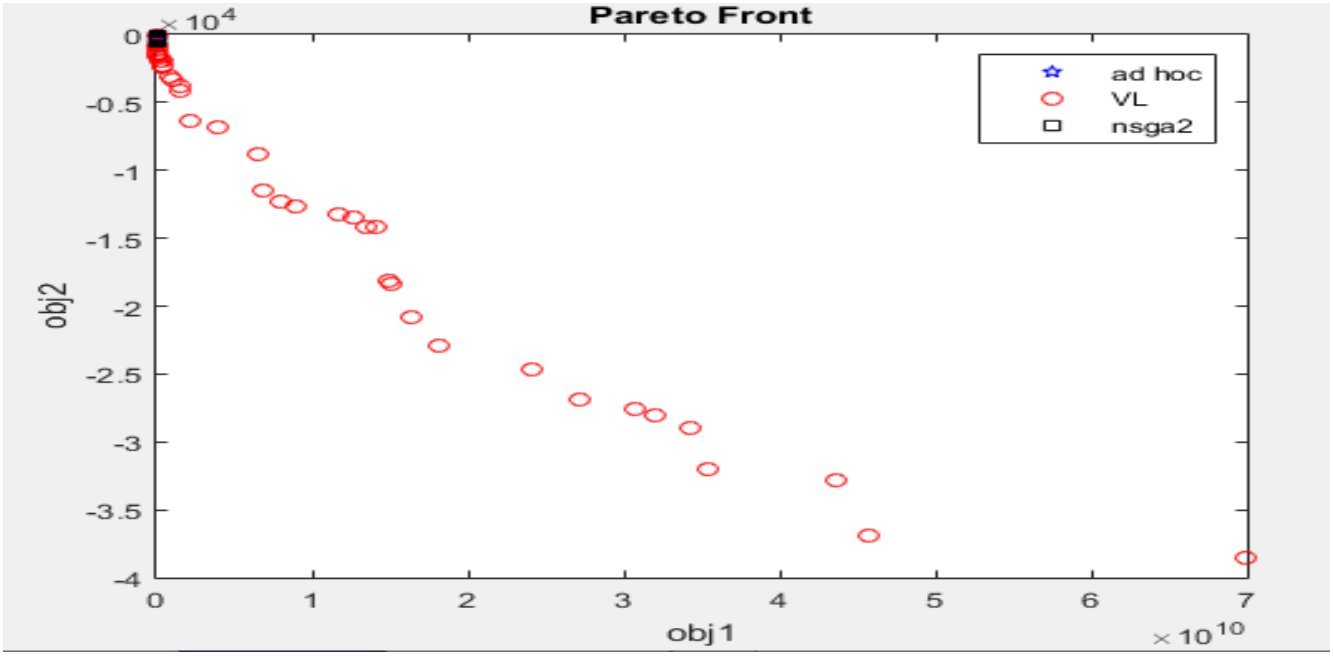


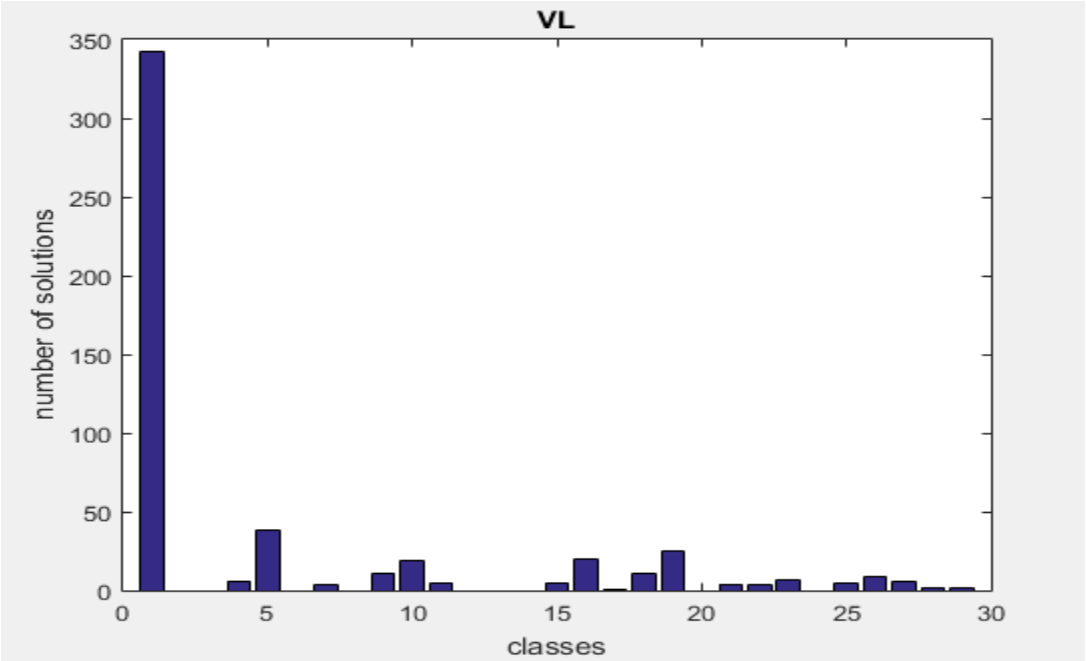


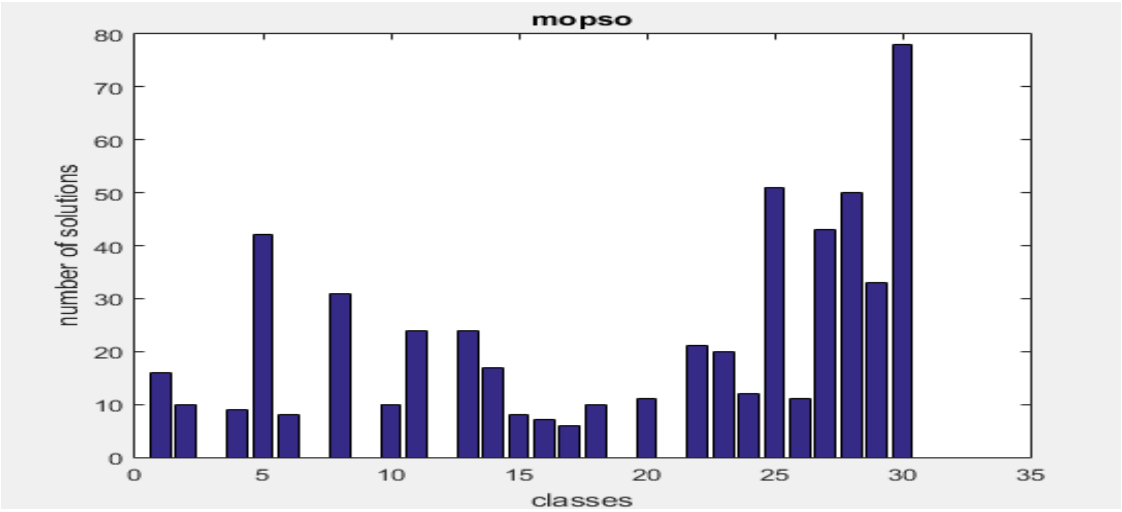

Relative Generational Distanse
×10^8
3
2.5
2
1.5
1
0.5
0
Fixed
Variable
nsga2

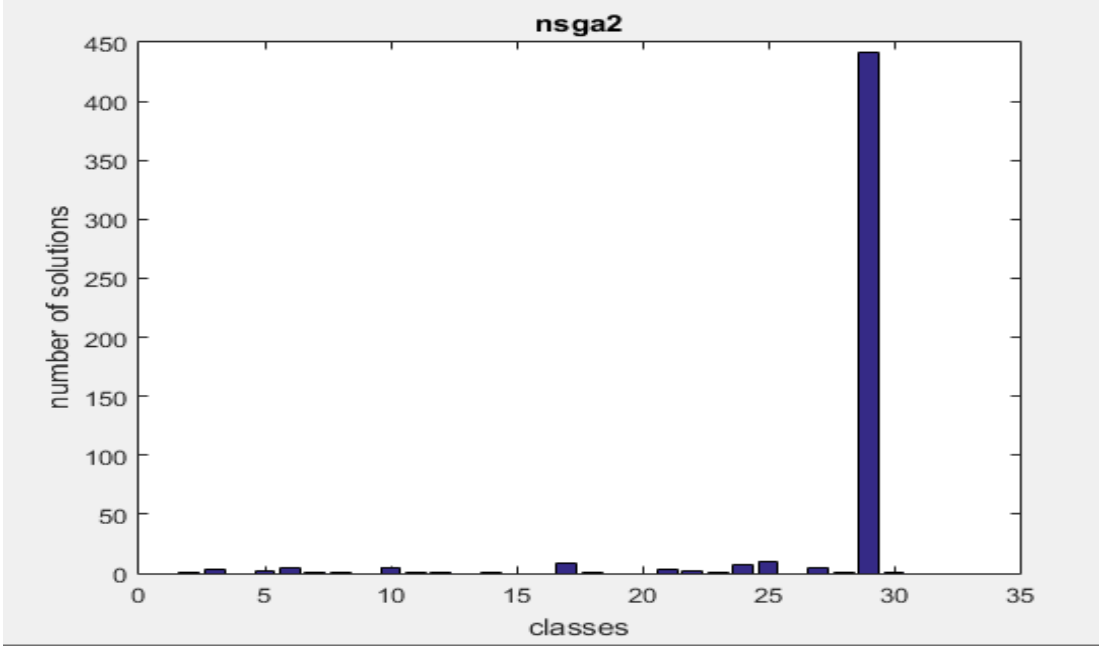

NDS
NDS
600
500
400
300
200
100
0
FL
VL
nsga2


HV
Hyper Volume
×10^15
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
FL
VL
nsga2


Pareto Front
× 10^4
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
-4
obj2
0
1
2
3
4
5
6
7
obj1
× 10^10
ad hoc
VL
nsga2


VL
number of solutions
classes
0
50
100
150
200
250
300
350
0
5
10
15
20
25
30


mopso
number of solutions
classes
0
10
20
30
40
50
60
70
80
0
5
10
15
20
25
30
35


nsga2
number of solutions
classes
0
50
100
150
200
250
300
350
400
450
0
5
10
15
20
25
30
35

Conclusion:

1- Superiorety ratio of VLMOPSO over MOPSO for all 9 experiments is 44.44%
2- Superiorety ratio of MOPSO over VLMOPSO for all 9 experiments is 33.33%
3- Superiorety ratio of VLMOPSO over NSGA2 for all 9 experiments is 66.67%
4- Superiorety ratio of NSGA2 over VLMOPSO for all 9 experiments is 22.22%
5- There is need to make the max length bigger to make vlmopso dominates over other algorithms
6- There is need to tune some parameters like minimum number of particles in the class for vlmopso
7- In these experiments I added mutation for MOPSO, there is need to delete it because MOPSO is benchmark algorithm
8- In these algorithms I didn't determine repository size in the last iteration in both MOPSO and VLMOPSO,
   So you can find that pareto front size sometimes is bigger than population size
9- In vlmopso , we minimize random objective in each iterations, thus we may minimize one objective more than other, and this may be the reason behind that vlmopso some times go forword the classes that minimize one objective vs other, so we need to minimize the objectives **Alternately**

The End

Eng.Mohammad Sakka