

## Laborator 4

### Functia Schwefel

Algoritm evolutiv pt minimizarea functiei Schwefel

#### Functia de fitness

```
def fitness(n, x):  
    f = 0  
    for i in range(n):  
        print("val x", x[i])  
        c = math.sqrt(abs(x[i]))  
        f = (-x[i]) * math.sin(c)  
    print("functia f", f)  
    return f
```

#### Functia de selectie flosita si in laboratorul trecut

```
def selectieTurnir(pop, popSize):  
    sample = np.random.default_rng().choice(popSize, size=5, replace=False)  
    best = pop[sample[0]].copy()  
    for i in sample:  
        if fitness(len(pop[i]), pop[i]) < fitness(len(best), best):  
            best = pop[i].copy()  
    return best
```

#### Functia de calcul a mediei

```
def mediePop(pop, n):  
    sum = 0.0  
  
    for i in range(0, len(pop)):  
  
        print("normal pop ", pop[i])  
        print("fitnss medie1", fitness(n, pop[i]))  
  
        sum = sum + fitness(n, pop[i])  
  
    medie = sum/len(pop)  
    print("best medie din fct", medie)  
    return medie
```

Functia de incrucisare convexa

```
def incrucisareConvexaSimpla(x, y, n):
    pos = np.random.randint(n)
    alpha = random.random()
    print(pos)
    print(alpha)
    xcopy = x.copy()
    ycopy = y.copy()
    for i in range(pos, n):
        x[i] = alpha * xcopy[i] + (1 - alpha) * ycopy[i]
        y[i] = alpha * ycopy[i] + (1 - alpha) * xcopy[i]

        if x[i] < MIN_INT:
            x[i] = MIN_INT
        if x[i] > MAX_INT:
            x[i] = MAX_INT
        if y[i] < MIN_INT:
            y[i] = MIN_INT
        if y[i] > MAX_INT:
            y[i] = MAX_INT

    return x, y
```

calculeaza valorile dupa formula de mai sus, in functie de alpha luat random

Functia de incrucisare medie

```
def incrucisareMedie(x, y, n):
    i = np.random.randint(n, size=2)
    print(i)
    xcopy = x.copy()
    x[i[0]] = (x[i[0]] + y[i[0]]) / 2
    y[i[0]] = (xcopy[i[0]] + y[i[0]]) / 2

    if x[i[0]] < MIN_INT:
        x[i[0]] = MIN_INT
    if x[i[0]] > MAX_INT:
        x[i[0]] = MAX_INT
    if y[i[0]] < MIN_INT:
        y[i[0]] = MIN_INT
    if y[i[0]] > MAX_INT:
        y[i[0]] = MAX_INT

    x[i[1]] = (x[i[1]] + y[i[1]]) / 2
    y[i[1]] = (xcopy[i[1]] + y[i[1]]) / 2

    if x[i[1]] < MIN_INT:
        x[i[1]] = MIN_INT
    if x[i[1]] > MAX_INT:
        x[i[1]] = MAX_INT
    if y[i[1]] < MIN_INT:
```

```

        y[i[1]] = MIN_INT
    if y[i[1]] > MAX_INT:
        y[i[1]] = MAX_INT

```

Returneaza 2 copii din cei 2 parinti, verificand daca rezultatele fac parte din domeniu

Mutatie gaussiana

```

def mutatie_gaussiana(x, t):
    SIGMA = 1 / (t + 1)
    MU = 0
    for i in range(len(x)):
        n = random.gauss(MU, SIGMA)
        if MIN_INT <= x[i] + n <= MAX_INT:
            x[i] += n

```

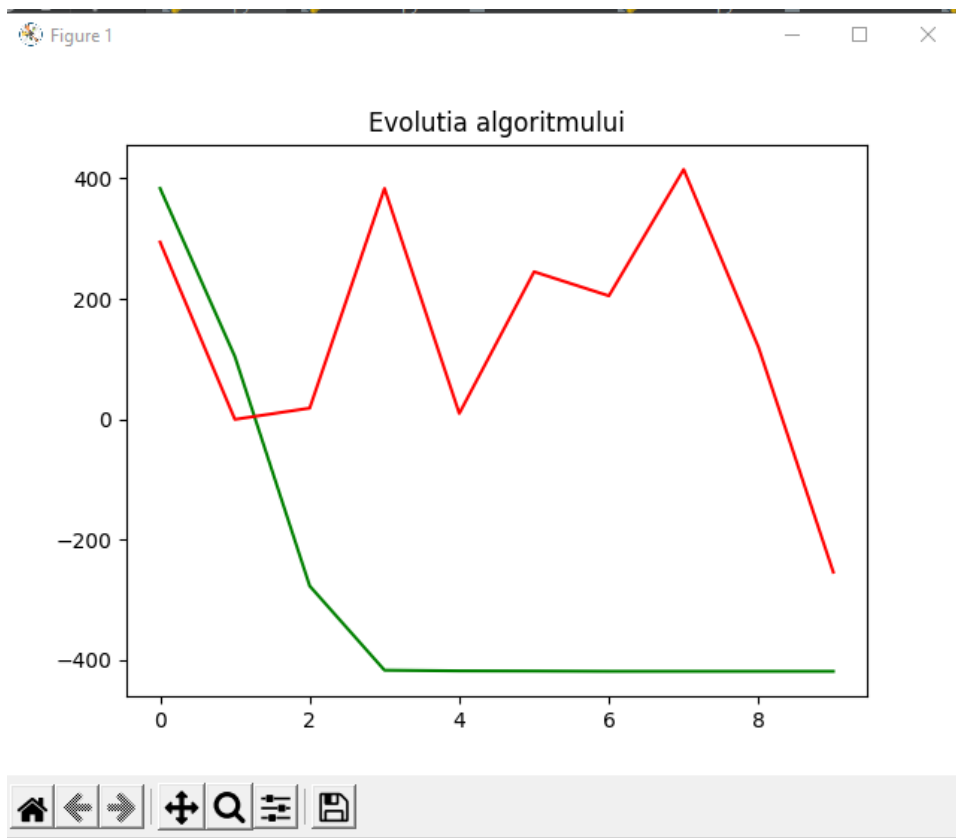
modificam valoarea adunand rezultatul functiei gaussiene, daca rezultatul functiei adunat la valoarea individului nu iese din domeniul functiei

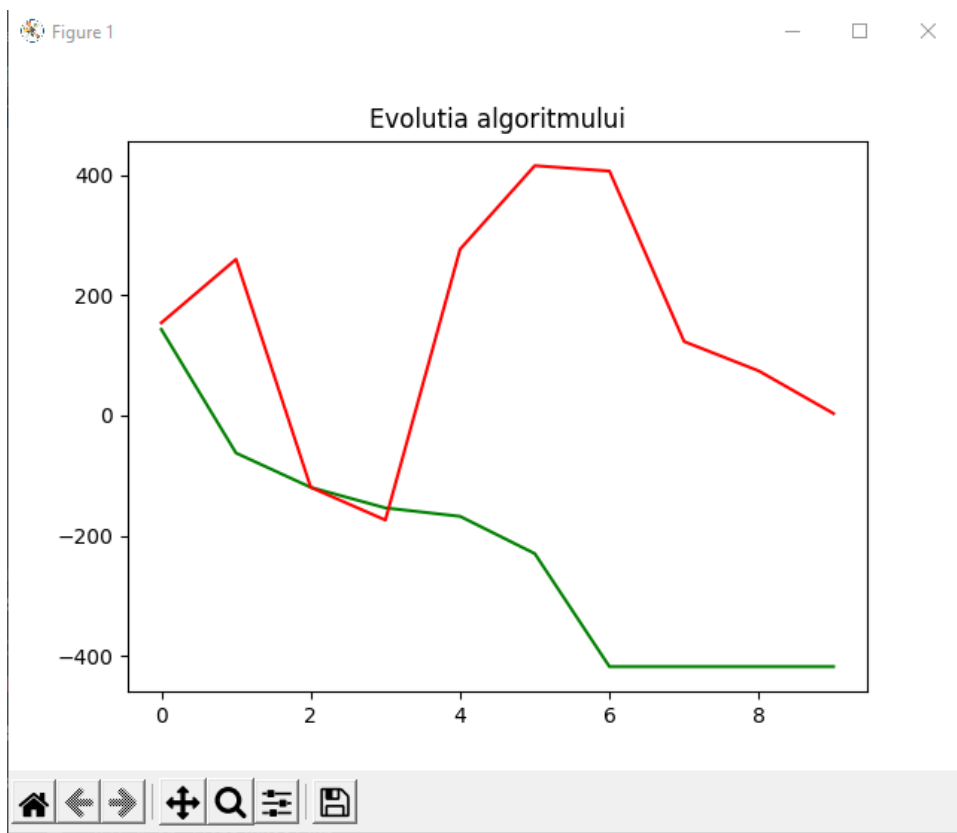
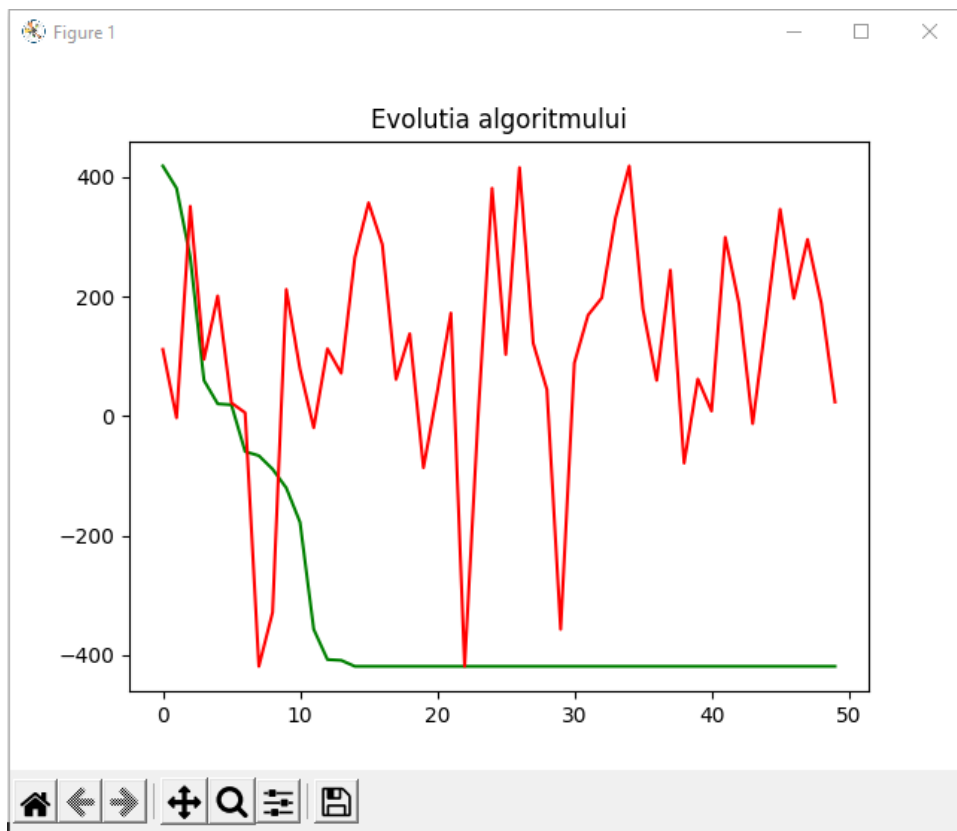
Functia principala, este aceeaasi functie de agoritm evolutiv folosita si in laboratorul 3, unde initializam populatia, initializam parintii, pe care ii incrucisam pentru a obtine copii, pe care apoi aplicam functiile de mutatie pentru a obtine copii mutanti, din care luam cele mai bune solutii

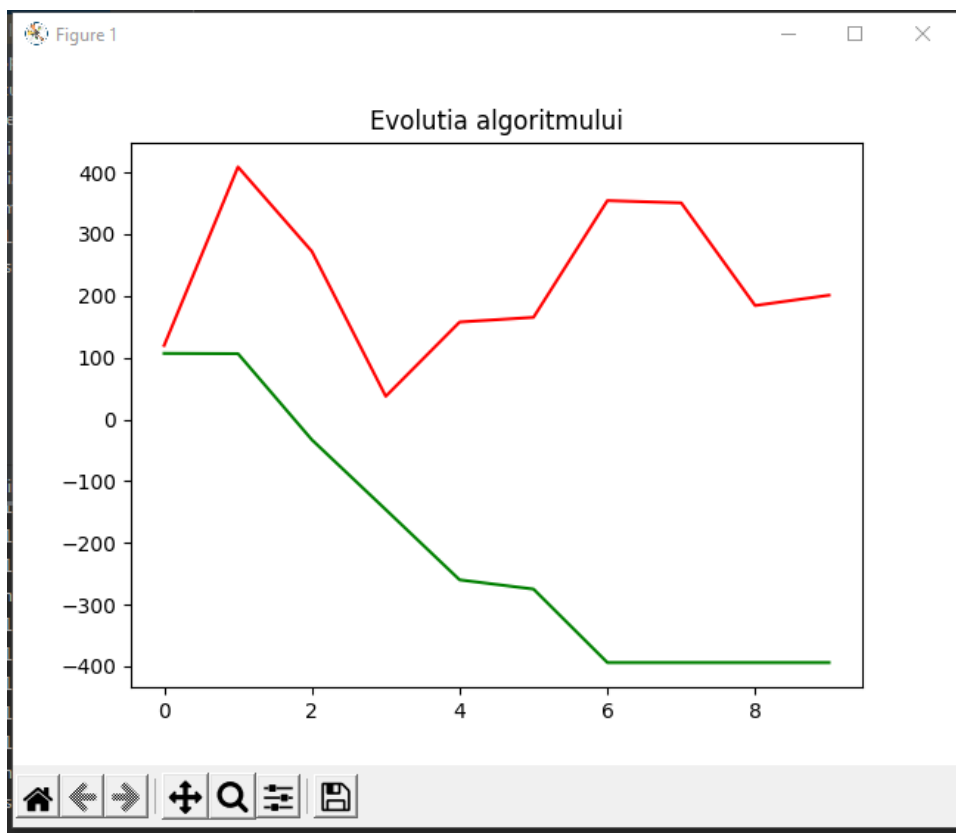
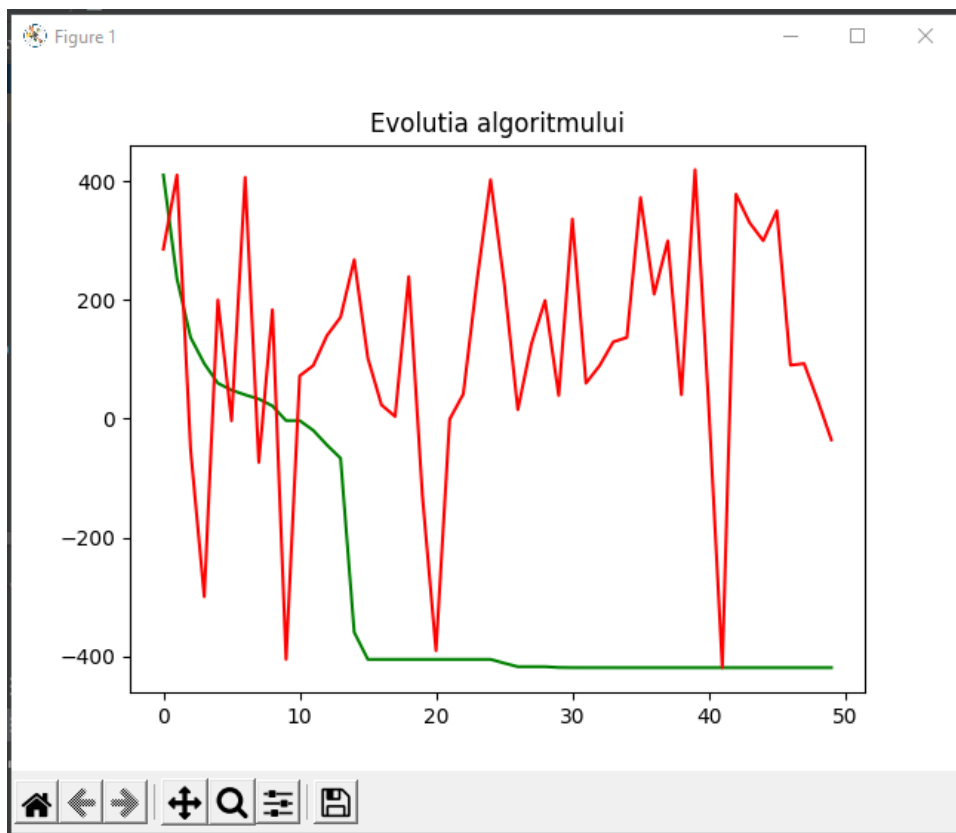
Executii	Incruisare	Mutatie	Dimensiune	Nr pop	Nr generatii	average	Timp	Best sol	Best average
10	convexa	gauss	5	10	10				
	convexa	uniforma	5	10	10	-239.4722 47475799 5	103.96 891880 0354	-418.97 267414 9225	-408.57 786857 97052
	convexa	gauss	5	10	50				
	convexa	uniforma	5	10	50	-272.2802 22098561	211.90 151047 706604	-418.93 869364 50739	-312.01 957399 78939
	medie	gauss	5	10	10				
	medie	uniforma	5	10	10	-165.8029 41639749 58		-394.03 712401 374986	-361.32 220590 34898
	medie	gauss	5	10	50				
	medie	uniforma	5	10	50	-235.5071 27525081 24	216.10 021567 344666	-417.10 771415 28115	-329.56 383125 07196
	convexa	gauss	10						

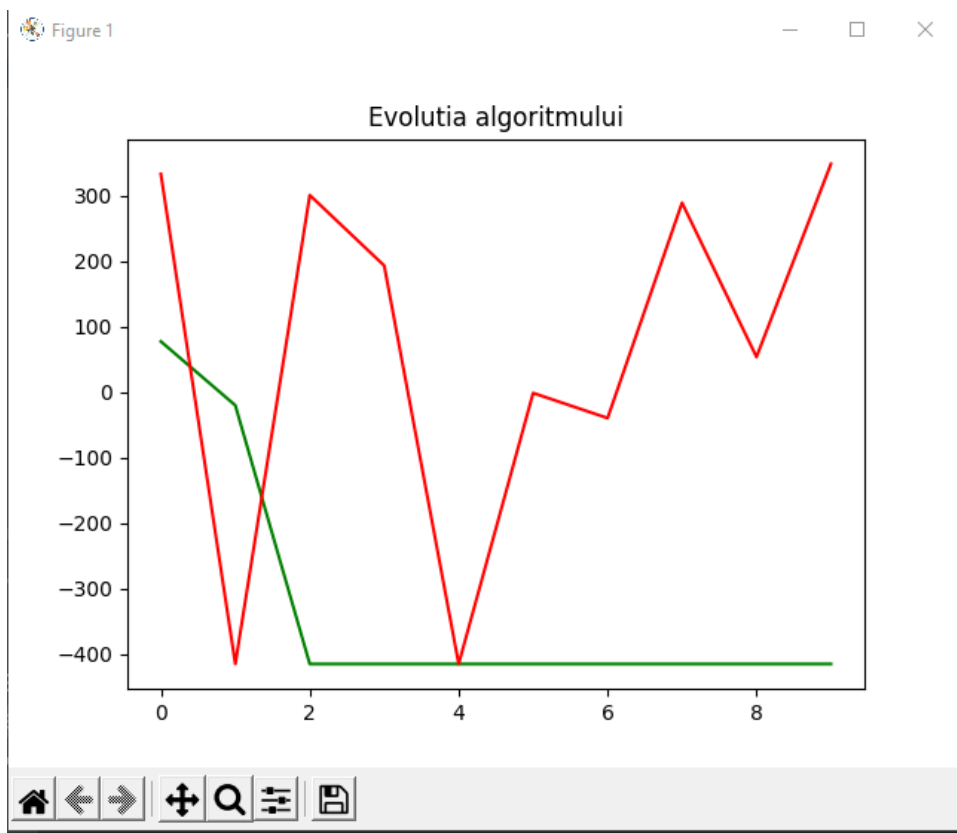
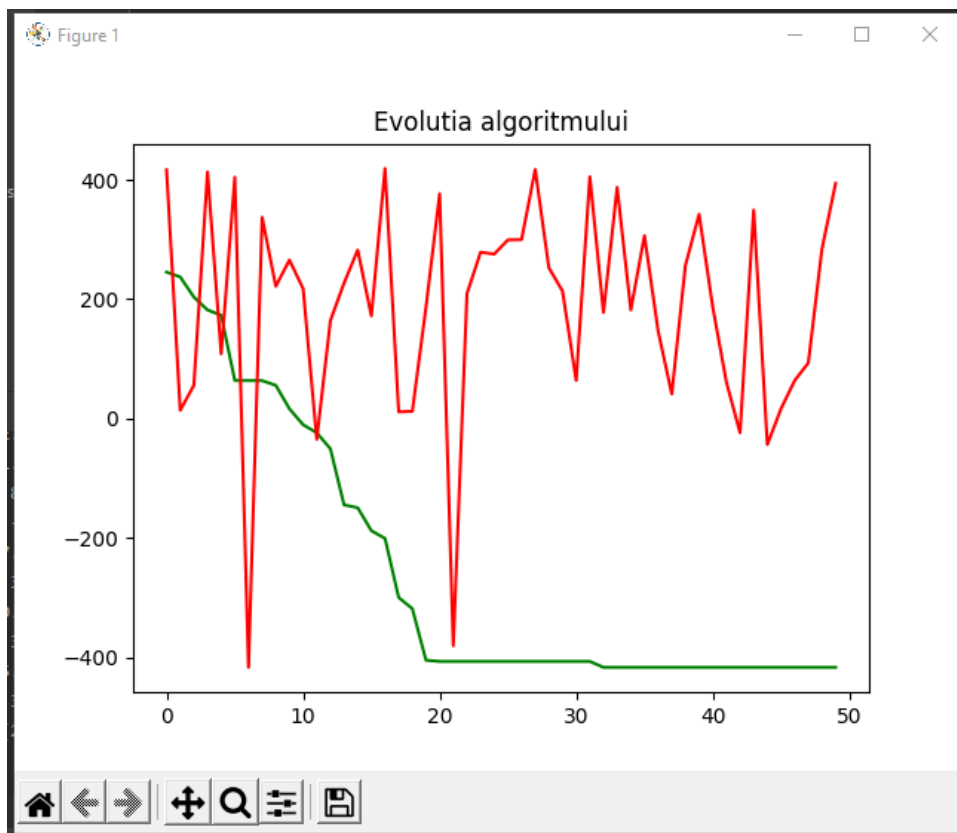
	convex a	uniform a	10	10	10	- 174.3119 10994182 03	66.014 678239 82239	- 417.68 373127 05427	- 252.13 677101 954312
	convex a	gauss	10						
	convex a	uniform a	10	10	50	- 272.9601 17536952 9	436.35 254073 143005	- 418.89 391919 121016	- 292.13 513090 91334
	medie	uniform a	10	10	10	- 283.5506 63044366	56.526 966094 9707	- 414.61 767578 430903	- 359.16 691589 635303
	medie	gauss	10	10	10				
	medie	gauss	10	10	50				
	medie	uniform a	10	10	50	- 265.6383 12632807 4	349.34 511184 69238	- 412.21 959894 74075	- 343.03 884052 30049

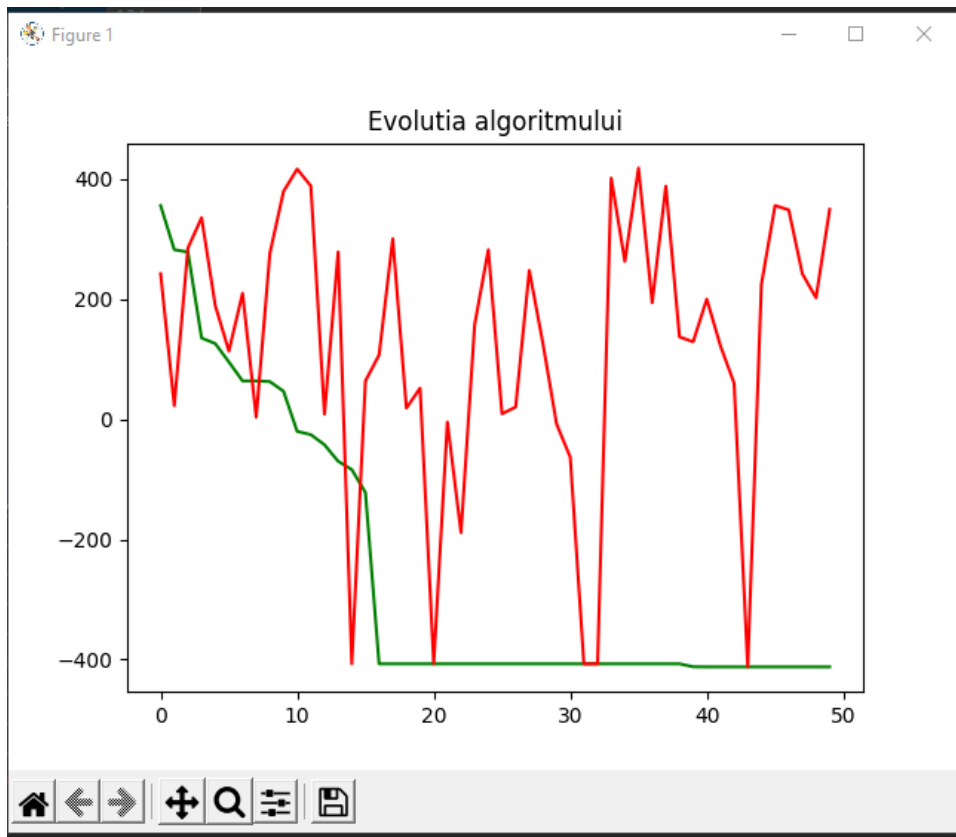
Observam ca avem cea mai buna solutie cand aplicam mutatia uniforma si incrucisarea convexa. Cand folosim mutatia uniforma si incrucisarea convexa cu dim 10, pop 10 si gen 50 ne apropiem cel mai tare de optimul global,  $f(x) = -n \cdot 418.9829$ ;  $x(i) = 420.9687$











## Swarm optimisation pso

Avem o clasa Particula, pentru a defini o particula. Avem attributele: pozitia, personal best, viteza fitness

```
class Particula:
    def __init__(self, n):
        self.viteza = [random.uniform(MIN_INT, MAX_INT) for _ in range(n)]
        self.pozitie = [random.uniform(MIN_INT, MAX_INT) for _ in range(n)]
        self.currentFitness = fitness(n, self.pozitie)
        self.pbest = 10000
```

Domeniul functiei

```
MIN_INT: float = -500
MAX_INT: float = 500
```

Avem metode de modificare a vitezei dupa formula din curs, de modificare a pozitiei si metoda de modificare personal best cu fitensul curent daca acesta e mai mic

```
def modificaViteza(self, gbest, w, c1, c2):
    for i in range(0, len(self.viteza)):
        self.viteza[i] = w * self.viteza[i] + c1 * random.random() * (self.pbest -
self.pozitie[i]) + c2 * random.random() * (gbest - self.pozitie[i])
```



```

def modificaPozitie(self):
    for i in range(0, len(self.pozitie)):
        self.pozitie[i] = self.pozitie[i] + self.viteza[i]

def update_pbest(self):
    if self.currentFitness < self.pbest:
        self.pbest = self.currentFitness

```

execut ii	dim	iterat ii	Nr part	w	c1	c2	best	medie	timp
10	5	10	10	1	2	2	- 19493. 934692 795396	- 8338.9 687624 19625	22.642 580270 767212
	5	10	50				- 143970 .94128 68937	- 67797. 196478 31551	22.393 128395 080566
	5	50	50				- 369062 481871 6.381	- 124162 747214 0.1501	26.624 576091 766357
	5	50	100				- 290483 483808 57.816	- 131228 470284 07.295	38.315 240383 14819
	10	10	10				- 11064. 093398 891122	- 7122.4 215443 90143	16.062 586545 944214
	10	50	50				- 233256 507632 4.5366	- 639505 955523 .675	30.331 240177 15454}
	10	50	100				- 453310 829525 22.2	- 138679 040637 69.355	60.886 889219 28406

Observam ca cu cat crestem dimensiunea, nr de iteratii si nr de particule incepem sa avem rezultate din ce in ce mai bune