Diferencialna evolucija realnih industrijskih izzivov CEC 2011

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Differential Evolution of Real World Industry Challenges CEC 2011

This paper presents a novel differential evolution algorithm for optimization of state-of-the-art real world optimization problems from industry on a world scale. The algorithm includes jDE as published in IEEE Transactions on Evolutionary Computation (2006) and Applied Intelligence (2008) as a base point and is extended with some of its existing improvements. In this paper we propose another extention, hybridization of multi-strategy ensemble with population reduction.

The problems optimized reflect most of the challenges in current industry problems tackled by optimization algorithms nowadays. We present results on all of the 22 problems included in the Problem Definitions for a competition on Congress on Evolutionary Computation (CEC) 2011. Performance of the proposed algorithm is compared to two competing algorithms at accompanying competition of the CEC conference.

1 Uvod

V članku predstavljamo nov optimizacijski algoritem diferencialne evolucije in ga ovrednotimo nad realnimi optimizacijskimi problemi. Naš algoritem je razširitev algoritma jDE s hibridizacijo več mutacijskih strategij in zmanjševanja populacije. Uporabljeni problemi za ovrednotenje kakovosti zajemajo aktualne industrijske izzive, ki so bili objavljeni v zadnjem času v revijah na temo optimizacije. Predstavljamo rezultate za vseh 22 problemov, vključenih v tehničnem poročilu [27]. Rezultate našega algoritma primerjamo še z rezultati dveh drugih algoritmov [15, 24], ki sta bila predstavljena na Congress on Evolutionary Computation 2011 v sekciji in tekmovanju optimizacije aktualnih dejanskih industrijskih izzivov.

V naslednjem poglavju podrobneje predstavimo sorodna dela. V tretjem poglavju opišemo predlagan razširjen algoritem diferencialne evolucije. V četrtem poglavju izvedemo eksperimente, opišemo rezultate in podamo primerjave. V petem poglavju podamo zaključek in predloge za nadaljnje delo.

2 Sorodna dela

Diferencialna evolucija[1] (DE) [26] je algoritem, ki se uspešno uporablja za globalno optimizacijo realno kodiranih numeričnih funkcij. Algoritem zaradi svoje narave prilagajanja problemu in stabilnosti iskanja z elitističnim selekcijskim mehanizmom daje boljše rezultate od ostalih evolucijskih algoritmov [4, 18, 21, 9]. Algoritem DE [26] je sestavljen iz glavne evolucijske zanke, v kateri z evolucijskimi operatorji mutacije, križanja in selekcije postopno in vzporedno izboljšuje približek iskane rešitve. Evolucijski operatorji vplivajo na vsak primerek $\mathbf{x}_i, \forall i \in [0, NP]$ v populaciji rešitev, iz katerih se zgradi nova populacija za naslednjo generacijo. Eno kreiranje novega osebka imenujemo iteracija, skupno število ovrednotenj posameznikov pa označimo s FEs.

2.1 Osnovni operatorji DE

V vsaki iteraciji operator mutacije izračuna mutiran vektor $\mathbf{v}_{i,G+1}$:

$$\mathbf{v}_{i,G+1} = \mathbf{x}_{r_1,G} + F \times (\mathbf{x}_{r_2,G} - \mathbf{x}_{r_3,G}),$$

kjer so $r_1, r_2, r_3 \in 1, 2, ..., NP$ paroma in od i različni indeksi primerkov iz populacije v generaciji G, $i \in 1, 2, ..., NP$ in $F \in [0, 2]$. Vektor z indeksom r_1 imenujemo osnovni vektor. Izraz $\mathbf{x}_{r_2,G} - \mathbf{x}_{r_3,G}$ imenujemo diferenčni vektor in po množenju s faktorjem ojačanja F, utežen diferenčni vektor.

Po mutaciji dobljeni mutiran vektor $\mathbf{v}_{i,G+1}$ križamo s ciljnim vektorjem $\mathbf{x}_{i,G}$ in tako dobimo poskusni vektor $\mathbf{u}_{i,G+1}$. Binarni operator križanja v algoritmu DE zapišemo kot:

$$u_{i,j,G+1} = \begin{cases} v_{i,j,G+1} & \text{rand}(0,1) \leq CR \text{ ali } j = j_{rand} \\ x_{i,j,G} & \text{sicer} \end{cases},$$

kjer $j \in [1, D]$ označuje j-ti iskalni parameter v prostoru z D dimenzijami, funkcija $\text{rand}(0,1) \in [0,1]$ označuje vzorčenje uniformno (psevdo) naključno porazdeljenega naključnega števila in j_{rand} izbira uniformno naključen indeks iskalnega parametra, ki ga vedno izmenjamo (da bi s tem preprečili izdelavo enakih posameznikov). CR označuje že omenjen krmilni parameter stopnje križanja.

[1] Morda bi bil primeren prevod tudi diferenčna evolucija.

2.2 Razširitve DE

Poznamo več različic in izboljšav osnovnega algoritma DE [9]. Obstaja tudi nekaj izboljšav osnovnih mutacijskih strategij [10, 31, 12, 2, 39, 8, 23, 19]. Algoritem DE je bil razširjen tudi z ansambli [35, 16]. Izboljšave diferencialne evolucije zajemajo tudi robustnost pri velikih dimenzijah iskalnega prostora [33, 36]. Križanje algoritma DE in evolucijskega programiranja [34] zasledimo v delu [32]. Algoritmu DE je soroden tudi algoritem optimizacije s kolonijami mravelj [14]. Bošković in sodelavci so diferencialno evolucijo uporabljali za uglaševanje parametrov iger s popolno informacijo in ničelno vsoto [3]. Algoritem DE je prav tako rotacijsko invarianten v prostoru spremenljivk [22]. Posledica tega je, da lahko dobro rešuje probleme z neločljivimi iskalnimi parametri. Takšno lastnost izkazuje precej realnih oz. industrijskih problemov [22, 11, 13, 28, 29, 40, 17, 30, 20]. Zaradi svoje uspešnosti je algoritem DE bil že večkrat uporabljen tudi za večkriterijsko optimizacijo [25, 37, 38].

Izmed obstoječih algoritmov smo izbrali algoritem jDE [7, 5, 6, 1]. Algoritem jDE vključuje mehanizem samoprilagajanja krmilnih parametrov F in CR, ki so ga uvedli Brest s sod. [4]. V začetni populaciji smo parametra inicializirali uniformno naključno. Slednji mehanizem uporablja zgoraj predstavljeno strategijo '*rand/1/bin*'. Mehanizem iz [4] samoprilagaja krmilna parametra F in CR med evolucijskim procesom; NP pa ostaja nespremenjen. Vsak posameznik v populaciji je bil razširjen z vrednostmi teh dveh samoprilagodljivih krmilnih parametrov. Njuni vrednosti se spreminjata:

$$F_{i,G+1} = \begin{cases} F_l + rand_1 \times F_u & \text{if } rand_2 < \tau_1, \\ F_{i,G} & \text{otherwise,} \end{cases} \tag{1}$$

$$CR_{i,G+1} = \begin{cases} rand_3 & \text{if } rand_4 < \tau_2, \\ CR_{i,G} & \text{otherwise.} \end{cases} \tag{2}$$

Novi vrednosti za F in CR se shranita v nov vektor. $rand_j, j \in \{1, 2, 3, 4\}$ so uniformno naključna števila $\in [0, 1]$. τ_1 in τ_2 predstavlja verjetnost prilagajanja obeh krmilnih parametrov F in CR. τ_1, τ_2, F_l, F_u imajo nespremenljive vrednosti $0,1,\ 0,1,\ 0,1,\ 0,9$. Nov F zavzema naključne vrednosti med $[0,1,\ 1]$ in nov CR med $[0,1]$. $F_{i,G+1}$ in $CR_{i,G+1}$ se izračunata pred mutacijo, po vzoru iz izkušenj ob razvoju evolucijskih strategij. Nova parametra tako vplivata na mutacijo, križanje in selekcijo novega vektorja $\mathbf{x}_{i,G+1}$.

V [5] je predstavljena razširitev algoritma jDE, ki razpolavlja velikost populacije, ko število generacij preseže razmerje med številom dovoljenih ovrednotenj in velikostjo populacije:

$$G_p > \frac{N_{max\_Feval}}{p_{max} NP_p}.$$

Tabela 1: Najboljša, najslabša, medialna in povprečna vrednost rezultatov ter standardna deviacija za 25 neodvisnih zagonov.

Fun.	FES	Najboljši	Najslabši	Medialni	Povprečni	Std. dev.
F1	50000	0.0000e+00	1.7799e+01	1.1490e+01	8.9712e+00	6.6038e+00
F1	100000	0.0000e+00	1.5504e+01	0.0000e+00	5.6703e+00	6.6475e+00
F1	150000	0.0000e+00	1.4779e+01	0.0000e+00	3.2413e+00	5.3550e+00
F2	50000	-2.0597e+01	-1.0832e+01	-1.5247e+01	-1.5485e+01	2.6507e+00
F2	100000	-2.5939e+01	-1.4016e+01	-2.0865e+01	-2.0938e+01	3.3790e+00
F2	150000	-2.7437e+01	-1.5980e+01	-2.3083e+01	-2.2199e+01	3.1082e+00
F3	50000	1.1515e-05	1.1515e-05	1.1515e-05	1.1515e-05	2.3171e-19
F3	100000	1.1515e-05	1.1515e-05	1.1515e-05	1.1515e-05	2.0275e-19
F3	150000	1.1515e-05	1.1515e-05	1.1515e-05	1.1515e-05	1.4748e-19
F4	50000	1.3771e+01	1.5085e+01	1.3771e+01	1.4101e+01	4.3475e-01
F4	100000	1.3771e+01	1.4329e+01	1.3771e+01	1.4016e+01	2.8287e-01
F4	150000	1.3771e+01	1.4993e+01	1.3771e+01	1.4021e+01	3.3774e-01
F5	50000	-3.4113e+01	-2.6199e+01	-3.2608e+01	-3.2154e+01	2.0651e+00
F5	100000	-3.4968e+01	-2.9172e+01	-3.4049e+01	-3.3345e+01	1.3924e+00
F5	150000	-3.6845e+01	-3.3244e+01	-3.4108e+01	-3.4358e+01	8.5992e-01
F6	50000	-2.9166e+01	-1.9512e+01	-2.2926e+01	-2.3221e+01	2.9840e+00
F6	100000	-2.9166e+01	-1.9512e+01	-2.7430e+01	-2.6451e+01	2.9505e+00
F6	150000	-2.9166e+01	-2.3006e+01	-2.7430e+01	-2.7277e+01	1.7513e+00
F7	50000	9.9186e-01	1.6383e+00	1.3196e+00	1.3113e+00	1.6973e-01
F7	100000	8.7249e-01	1.5562e+00	1.1732e+00	1.1575e+00	1.7048e-01
F7	150000	7.7663e-01	1.4018e+00	1.0717e+00	1.0733e+00	1.5427e-01
F8	50000	2.2000e+02	2.2000e+02	2.2000e+02	2.2000e+02	0.0000e+00
F8	100000	2.2000e+02	2.2000e+02	2.2000e+02	2.2000e+02	0.0000e+00
F8	150000	2.2000e+02	2.2000e+02	2.2000e+02	2.2000e+02	0.0000e+00
F9	50000	3.2449e+03	1.9215e+04	9.7916e+03	1.0338e+04	4.8414e+03
F9	100000	1.3586e+03	6.4690e+03	2.8214e+03	3.0953e+03	1.2028e+03
F9	150000	1.8620e+03	4.1711e+03	2.4700e+03	2.6687e+03	7.0083e+02
F10	50000	-2.1348e+01	-1.2458e+01	-1.7711e+01	-1.7545e+01	3.3356e+00
F10	100000	-2.1507e+01	-1.3665e+01	-2.1313e+01	-2.0577e+01	1.8769e+00
F10	150000	-2.1718e+01	-2.0929e+01	-2.1309e+01	-2.1301e+01	1.5658e-01
F11	50000	3.1363e+05	1.1372e+06	7.0705e+05	6.8015e+05	2.1149e+05
F11	100000	5.4059e+04	4.0692e+05	2.2014e+05	2.2301e+05	9.7889e+04
F11	150000	5.1789e+04	4.5118e+05	1.1017e+05	1.3713e+05	9.8358e+04
F12	50000	1.1174e+06	1.8389e+06	1.4543e+06	1.4802e+06	1.7720e+05
F12	100000	1.0795e+06	1.3428e+06	1.1317e+06	1.1366e+06	5.3778e+04
F12	150000	1.0702e+06	1.1431e+06	1.0869e+06	1.0906e+06	1.7183e+04
F13	50000	1.5445e+04	1.5483e+04	1.5454e+04	1.5458e+04	1.0919e+01
F13	100000	1.5445e+04	1.5477e+04	1.5447e+04	1.5450e+04	7.8227e+00
F13	150000	1.5444e+04	1.5463e+04	1.5445e+04	1.5447e+04	4.5126e+00
F14	50000	1.8670e+04	1.9286e+04	1.8946e+04	1.8942e+04	1.5497e+02
F14	100000	1.8545e+04	1.9121e+04	1.8862e+04	1.8846e+04	1.4143e+02
F14	150000	1.8433e+04	1.8937e+04	1.8650e+04	1.8665e+04	1.2668e+02
F15	50000	3.2845e+04	3.3045e+04	3.2942e+04	3.2941e+04	5.1494e+01
F15	100000	3.2798e+04	3.2998e+04	3.2875e+04	3.2890e+04	5.2627e+01
F15	150000	3.2755e+04	3.2933e+04	3.2857e+04	3.2855e+04	4.9451e+01
F16	50000	1.3171e+05	1.5171e+05	1.4069e+05	1.4097e+05	5.3754e+03
F16	100000	1.3037e+05	1.4671e+05	1.3996e+05	1.3948e+05	4.0012e+03
F16	150000	1.3086e+05	1.4293e+05	1.3526e+05	1.3547e+05	3.1875e+03
F17	50000	1.9152e+06	3.1887e+06	2.2010e+06	2.2958e+06	3.7900e+05
F17	100000	1.9264e+06	3.0489e+06	2.1246e+06	2.2196e+06	3.4243e+05
F17	150000	1.9241e+06	3.0383e+06	2.0043e+06	2.1424e+06	2.8890e+05
F18	50000	9.4234e+05	1.2355e+06	9.5300e+05	9.8982e+05	7.9856e+04
F18	100000	9.3772e+05	1.2523e+06	9.4673e+05	9.7131e+05	7.3085e+04
F18	150000	9.4021e+05	9.8663e+05	9.4511e+05	9.4944e+05	1.1790e+04
F19	50000	1.0660e+06	1.7581e+06	1.4172e+06	1.4211e+06	1.8908e+05
F19	100000	1.1330e+06	1.7967e+06	1.3362e+06	1.3796e+06	1.6721e+05
F19	150000	1.0811e+06	1.7819e+06	1.3939e+06	1.3569e+06	1.7197e+05
F20	50000	9.4234e+05	1.2355e+06	9.5300e+05	9.8982e+05	7.9856e+04
F20	100000	9.3772e+05	1.2523e+06	9.4673e+05	9.7131e+05	7.3085e+04
F20	150000	9.4021e+05	9.8663e+05	9.4511e+05	9.4944e+05	1.1790e+04
F21	50000	1.2125e+01	2.7129e+01	1.8808e+01	1.9064e+01	2.8338e+00
F21	100000	9.9501e+00	2.1351e+01	1.8333e+01	1.7495e+01	2.6651e+00
F21	150000	1.1078e+01	2.2740e+01	1.7559e+01	1.7043e+01	2.4579e+00
F22	50000	1.1149e+01	2.2490e+01	1.8486e+01	1.7846e+01	3.2014e+00
F22	100000	9.5913e+00	2.0399e+01	1.4753e+01	1.4698e+01	2.9722e+00
F22	150000	8.9134e+00	1.6576e+01	1.3344e+01	1.3079e+01	2.2968e+00

3 Hibridizacija ansamblov več strategij z zmanjševanjem populacije pri jDE

V algoritem jDE [4, 5] smo vključili ob zmanjševanju populacije še dve strategiji, rand/1/bin in best/1/bin. Prvo strategijo smo izvajali, ko je bila populacija večja od 100, sicer v polovici primerov. Drugo strategijo smo izvajali v preostalih primerih in ji dodali malenkostno naključno variacijo (Δ=1e-15) nespremenjenih komponent poskusnega vektorja. Velikost začetne populacije (NP) smo nastavili na 200 in število delitev populacije ($pmax$) na 4.

4 Rezultati

Algoritem smo preizkusili na ogrodju izzivov za tekmovanje na Congress on Evolutionary Computation (CEC) 2011 [27]. Uporabili smo različico za Linux, ki

Tabela 2: Primerjava povprečnih najboljših vrednosti za 25 neodvisnih zagonov našega in drugih algoritmov.

Fun.	FES	aDE-v1	C-0362	C-0508	diff(C-0362)	diff(C-0508)
F1	50000	8.9712e+00	7.06E+00	2.1870E+00	*1.9112e+00*	*6.7842e+00*
F1	100000	5.6703e+00	2.29E+00	1.0978E+00	*3.3803e+00*	*4.5725e+00*
F1	150000	3.2413e+00	1.78E+00	8.7697E-01	*1.4613e+00*	*2.3643e+00*
F2	50000	-1.5485e+01	-1.26E+01	-2.6525E+01	**-2.8850e+00**	*1.1040e+01*
F2	100000	-2.0938e+01	-1.64E+01	-2.7527E+01	**-4.5380e+00**	*6.5890e+00*
F2	150000	-2.2199e+01	-1.83E+01	-2.7731E+01	**-3.8990e+00**	*5.5320e+00*
F3	50000	1.1515e-05	1.15E-05	1.1515E-05	*1.5000e-08*	0.0000e+00
F3	100000	1.1515e-05	1.15E-05	1.1515E-05	*1.5000e-08*	0.0000e+00
F3	150000	1.1515e-05	1.15E-05	1.1515E-05	*1.5000e-08*	0.0000e+00
F4	50000	1.4101e+01	1.67E+01	1.9524E+01	**-2.5990e+00**	**-5.4230e+00**
F4	100000	1.4016e+01	1.67E+01	1.9343E+01	**-2.6840e+00**	**-5.3270e+00**
F4	150000	1.4021e+01	1.67E+01	1.7339E+01	**-2.6790e+00**	**-3.3180e+00**
F5	50000	-3.2154e+01	-2.38E+01	-3.2358E+01	**-8.3540e+00**	*2.0400e-01*
F5	100000	-3.3345e+01	-2.75E+01	-3.4237E+01	**-5.8450e+00**	*8.9200e-01*
F5	150000	-3.4358e+01	-2.90E+01	-3.4720E+01	**-5.3580e+00**	*3.6200e-01*
F6	50000	-2.3221e+01	-1.28E+01	-3.2239E+01	**-1.0421e+01**	*9.0180e+00*
F6	100000	-2.6451e+01	-1.55E+01	-3.4183E+01	**-1.0951e+01**	*7.7320e+00*
F6	150000	-2.7277e+01	-1.70E+01	-3.5033E+01	**-1.0277e+01**	*7.7560e+00*
F7	50000	1.3113e+00	1.61E+00	9.8858E-01	**-2.9870e-01**	*3.2272e-01*
F7	100000	1.1575e+00	1.49E+00	9.2967E-01	**-3.3250e-01**	*2.2783e-01*
F7	150000	1.0733e+00	1.42E+00	8.8477E-01	**-3.4670e-01**	*1.8853e-01*
F8	50000	2.2000e+02	2.20E+02	2.2000E+02	0.0000e+00	0.0000e+00
F8	100000	2.2000e+02	2.20E+02	2.2000E+02	0.0000e+00	0.0000e+00
F8	150000	2.2000e+02	2.20E+02	2.2000E+02	0.0000e+00	0.0000e+00
F9	50000	1.0338e+04	2.875E+03	4.5612E+05	*7.4630e+03*	**-4.4578e+05**
F9	100000	3.0953e+03	2.529E+03	3.4660E+05	*5.6630e+02*	**-3.4350e+05**
F9	150000	2.6687e+03	2.529E+03	3.3547E+05	*1.3970e+02*	**-3.3280e+05**
F10	50000	-1.7545e+01	-1.52E+01	-1.6736E+01	**-2.3450e+00**	**-8.0900e-01**
F10	100000	-2.0577e+01	-1.55E+01	-1.6751E+01	**-5.0770e+00**	**-3.8260e+00**
F10	150000	-2.1301e+01	-1.56E+01	-1.6756E+01	**-5.7010e+00**	**-4.5450e+00**
F11	50000	6.8015e+05	5.26E+04	4.7747E+04	*6.2755e+05*	*6.3240e+05*
F11	100000	2.2301e+05	5.24E+04	4.6423E+04	*1.7061e+05*	*1.7659e+05*
F11	150000	1.3713e+05	5.22E+04	4.6321E+04	*8.4930e+04*	*9.0809e+04*
F12	50000	1.4802e+06	1.08E+06	1.1586E+06	*4.0020e+05*	*3.2160e+05*
F12	100000	1.1366e+06	1.07E+06	1.0498E+06	*6.6600e+04*	*8.6800e+04*
F12	150000	1.0906e+06	1.07E+06	1.0490E+06	*2.0600e+04*	*4.1600e+04*
F13	50000	1.5458e+04	1.55E+04	1.5446E+04	**-4.2000e+01**	*1.2000e+01*
F13	100000	1.5450e+04	1.55E+04	1.5446E+04	**-5.0000e+01**	*4.0000e+00*
F13	150000	1.5447e+04	1.55E+04	1.5446E+04	**-5.3000e+01**	*1.0000e+00*
F14	50000	1.8942e+04	1.82E+04	1.8099E+04	*7.4200e+02*	*8.4300e+02*
F14	100000	1.8846e+04	1.82E+04	1.8098E+04	*6.4600e+02*	*7.4800e+02*
F14	150000	1.8665e+04	1.81E+04	1.8096E+04	*5.6500e+02*	*5.6900e+02*
F15	50000	3.2941e+04	3.28E+04	3.2850E+04	*1.4100e+02*	*9.1000e+01*
F15	100000	3.2890e+04	3.28E+04	3.2816E+04	*9.0000e+01*	*7.4000e+01*
F15	150000	3.2855e+04	3.27E+04	3.2790E+04	*1.5500e+02*	*6.5000e+01*
F16	50000	1.4097e+05	1.32E+05	1.2440E+05	*8.9700e+03*	*1.6570e+04*
F16	100000	1.3948e+05	1.31E+05	1.2400E+05	*8.4800e+03*	*1.5480e+04*
F16	150000	1.3547e+05	1.31E+05	1.2389E+05	*4.4700e+03*	*1.1580e+04*
F17	50000	2.2958e+06	1.92E+06	1.8653E+06	*3.7580e+05*	*4.3050e+05*
F17	100000	2.2196e+06	1.92E+06	1.8391E+06	*2.9960e+05*	*3.8050e+05*
F17	150000	2.1424e+06	1.92E+06	1.8386E+06	*2.2240e+05*	*3.0380e+05*
F18	50000	9.8982e+05	9.44E+05	9.2533E+05	*4.5820e+04*	*6.4490e+04*
F18	100000	9.7131e+05	9.43E+05	9.2442E+05	*2.8310e+04*	*4.6890e+04*
F18	150000	9.4944e+05	9.43E+05	9.2393E+05	*6.4400e+03*	*2.5510e+04*
F19	50000	1.4211e+06	9.94E+05	9.3282E+05	*4.2710e+05*	*4.8828e+05*
F19	100000	1.3796e+06	9.91E+05	9.3061E+05	*3.8860e+05*	*4.4899e+05*
F19	150000	1.3569e+06	9.90E+05	9.3001E+05	*3.6690e+05*	*4.2689e+05*
F20	50000	9.8982e+05	9.44E+05	9.2710E+05	*4.5820e+04*	*6.2720e+04*
F20	100000	9.7131e+05	9.43E+05	9.2436E+05	*2.8310e+04*	*4.6950e+04*
F20	150000	9.4944e+05	9.43E+05	9.2382E+05	*6.4400e+03*	*2.5620e+04*
F21	50000	1.9064e+01	2.26E+01	1.6943E+01	**-3.5360e+00**	*2.1210e+00*
F21	100000	1.7495e+01	1.98E+01	1.5888E+01	**-2.3050e+00**	*1.6070e+00*
F21	150000	1.7043e+01	1.88E+01	1.5360E+01	**-1.7570e+00**	*1.6830e+00*
F22	50000	1.7846e+01	1.99E+01	2.0483E+01	**-2.0540e+00**	**-2.6370e+00**
F22	100000	1.4698e+01	1.57E+01	1.6422E+01	**-1.0020e+00**	**-1.7240e+00**
F22	150000	1.3079e+01	1.39E+01	1.4909E+01	**-8.2100e-01**	**-1.8300e+00**

je spisana v C++ in ovija okolje Matlab. V ogrodju je zajetih 22 raznolikih funkcij, ki so skozi ovoj izpostavljene kot funkcije brez omejitev. Omejitve, ki jih je potrebno upoštevati pri optimizaciji izzivov, so vključene v ustreznostni funkciji.

Rezultati optimizacije za 25 neodvisnih zagonov so v tabeli 1. Primerjavo rezultatov algoritma z drugimi vidimo v tabeli 2, kjer so v tretji koloni povprečne vrednosti končnih rezultatov našega algoritma, v četrti algoritma avtorjev Mallipeddi in Suganthan z oznako C-0362 [15] in peti algoritma avtorjev Reynoso-Meza s sod. z oznako C-0508 [24]. V šesti in sedmi koloni sta navedeni razliki med našim in vsakim od primerjanih algoritmomov. Kot vidimo iz primerjave, je naš algoritem od prvega boljši na 9 problemih, slabši na 12 in na 1 problemu ni razlik v rezultatih. Glede na drug algoritem je naš boljši na 4 problemih, slabši na 16 in na 2 problemih ni razlik v rezultatih.

5 Zaključek

Predstavili smo algoritem za optimizacijo 22 realnih industrijskih izzivov iz letošnjega tekmovanja na Congress on Evolutionary Computation (CEC) 2011. Predstavljen algoritem sloni na algoritmu jDE in ga razširja s hibridizacijo ansamblov več strategij z zmanjševanjem populacije.
V nadaljevanju raziskovalnega dela nameravamo dodatno izboljšati predstavljen algoritem s prilagajanjem velikosti populacije.

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