Control Parameter Adaptation in Differential Evolution

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Doctoral Thesis Summary

Tomas Bata University in Zlín

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Faculty of Applied Informatics

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Adaptace kontrolních parametrů v diferenciální evoluci

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ABSTRAKT

Tato práce popisuje autorovu výzkumnou aktivitu v oblasti adaptivních variant algoritmu diferenciální evoluce pro optimalizaci jednokriteriálních funkcí definovaných ve spojitém prostoru. První část této práce popisuje oblast matematické optimalizace a její rozdělení do jednotlivých podkategorií podle charakteristik optimalizované funkce. Zároveň je v této části popsán typický zástupce metaheuristické optimalizace - evoluční výpočetní techniky.
Druhá část této práce se věnuje variantám algoritmu diferenciální evoluce včetně variant s adaptivními kontrolními parametry. V této části se autor věnuje i důvodům, proč si vybral algoritmus Success-History based Adaptive Differential Evolution jako základ své vědecké práce.
V experimentální části práce je navržen nástroj pro analýzu dynamiky populace evolučních algoritmů. Ten může být využit jak při tvorbě nových, tak i pro vyhodnocení vlastností stávajících a aktuálně používaných algoritmů. Mimo analýzu dynamiky populace obecně se autor zaměřil i na konkrétní algoritmy založené na diferenciální evoluci. Navrhl dvě úpravy vnitřní dynamiky - multi–chaotický framework pro výběr rodičů a adaptace kontrolních parametrů s využitím vzdálenosti jedinců. Obě techniky jsou zaměřeny na pomoc s hledáním správné rovnováhy mezi prohledáváním prostoru řešení do šířky a do hloubky. Na příkladu moderní verze diferenciální evoluce ve variantě jSO je ukázán přínos implementace adaptace kontrolních parametrů s využitím vzdálenosti jedinců. Takto upravený algoritmus byl nazván DISH a byl otestován na testovacích sadách spojených s celosvětovým kongresem evolučních technik - CEC (Congress on Evolutionary Computation). Výsledky ukazují, že využití nové adaptační strategie je vhodné především pro úlohy, které optimalizují větší množství vstupních parametrů.
Praktické využití algoritmu DISH je demonstrováno na příkladu hledání optimálního rozmístění spaloven odpadu v České republice.
Výše zmíněné výsledky ukazují, že i v rámci jednoduchých změn vnitřní dynamiky algoritmu lze dosáhnout lepší výkonnosti. I proto si autor zvolil jako svůj budoucí výzkumný směr rozvíjení nástroje pro analýzu vnitřní populační dynamiky metaheuristických algoritmů.

ABSTRACT

This doctoral thesis summary describes the author's research in the area of adaptive Differential Evolution variants for small–scale continuous single–objective optimization. The first part describes the topic of mathematical optimization and lists various problem domains according to the problem characteristics. It also describes the area of metaheuristic optimization and Evolutionary Computation Techniques.
The Differential Evolution algorithm variants and control parameter adaptivity are described in the next part of this work and it also provides the justification of selecting Success–History based Adaptive Differential Evolution algorithm as a basis for author's research focus.
A novel population dynamic analysis tool is proposed in the experimental part. This tool can be used for the development process of new metaheuristic techniques as well as for the analysis of the state-of-the-art methods.
The experimental part also provides the proposal of multi–chaotic framework for parent selection for the Differential Evolution based algorithms and Distance based parameter adaptation, which can be implemented into adaptive variants of Differential Evolution algorithm to improve the balance between exploration and exploitation. The benefits of using Distance based parameter adaptation are shown on the improved jSO algorithm - DISH. The performance of both versions (jSO and DISH) is compared on the basis of Congress on Evolutionary Computation benchmark sets and shows that the DISH variant is more suitable for optimization problems of a larger scale.
The practical use of the DISH algorithm is demonstrated on the operations research problem of finding optimal dislocation of waste–to–energy facilities in the Czech Republic.
Through the above–mentioned results, it can be seen that even simple changes in algorithms' inner dynamic can lead to significant improvements. Therefore, the research area of adaptive metaheuristics for optimization can benefit from knowledge gained through thorough algorithm analysis, which is the author's chosen research direction for the future.

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1 INTRODUCTION

Mathematical optimization is a scientific research area that deals with searching for the problem parameter values combination that would yield the best result – objective function value (e.g., minimization of a cost or maximization of a profit). Of course, there are multiple subcategories of optimization tasks that require appropriate methods for their solving. These categories are divided according to [1] as follows:

- **The number of objectives:**
  - **Single–objective optimization** – the goal is to optimize one objective.
  - **Multi–objective optimization** – the goal is to simultaneously optimize two or three objectives.
  - **Many–objective optimization** – the goal is to simultaneously optimize more than three objectives.
- **The input parameter type:**
  - **Discrete / Combinatorial optimization** – optimized parameters have a finite number of possible values.
  - **Continuous / Real–valued / Numerical optimization** – optimized parameters are real–valued.
- **The computational complexity of the objective function:**
  - **Expensive optimization** – it is computationally expensive to evaluate the objective function of a single solution.
  - **Non–expensive optimization** – it is computationally inexpensive to evaluate the objective function of a single solution.
- **The search space type:**
  - **Unconstrained optimization** – the search space of parameter values is infinite.

- **Bound–constrained optimization** – the search space is not constrained; individual parameters have only upper and lower bounds.
- **Constrained optimization** – the search space is constrained by additional equalities or inequalities.

- **The scale of the problem (number of optimized parameters / dimensionality):**
  - **Small-scale optimization** – the dimensionality of the problem is between 1 and 100.
  - **Large-scale optimization** – the dimensionality of the problem is in hundreds or thousands.

Optimization algorithms are methods for solving optimization problems and can also be classified into subcategories. One of the main classifications might be by algorithms stochasticity into two groups - deterministic and stochastic [2]. Deterministic algorithms follow a rigorous mathematical approach and work with the mathematical model of the problem to provide the optimal solution. Unfortunately, the most complex tasks are unsolvable by deterministic optimization algorithms due to the time and computational constraints. Thus, stochastic optimization algorithms that use randomness in their core are employed. These algorithms can also be titled metaheuristics. Metaheuristics treat optimization problems as black boxes - trying to solve optimization tasks using only the information of an input/output combination and learning from that. Due to their stochastic nature, metaheuristics do not guarantee a finding of the global optimum.
Evolutionary Computational Techniques (ECTs) form a particular metaheuristic class based on the principle of natural selection and are described in the next section.

1.1 Evolutionary computational techniques in optimization

ECTs are part of the soft computing field and are based on the Darwinian theory of evolution [3]. In this sense, ECTs often work with a population of individuals. Those individuals are combined via crossover operator (an analogy with breeding), and the resulting individuals are further mutated via mutation operator (analogous to gene mutation) to provide possibly fitter offspring for the next generation. This process is applied to the whole population to provide a new generation of solutions to the given optimization task. Thanks to this, ECTs can be used to optimize particularly hard optimization tasks that could not be solved, due to the computational complexity, by traditional deterministic methods.

One of the problems while using ECTs is a requirement for a control parameter setting. These parameters can significantly impact the algorithm's performance, and therefore their correct setting is essential. One of the latest trends in ECTs is to address this problem by adapting the algorithm's behavior (via adapting control parameter values) to the given optimization task. With the famous No Free Lunch (NFL) theorem in mind [4], adaptive algorithms try to overcome the problem of correct parameter setting by incorporating knowledge of previously successful values of these parameters into the evolution process in an intelligent way. Thus, the user is no longer obliged to fine–tune these parameters manually.

The Differential Evolution (DE) algorithm [5] is one of the main representatives of ECTs and has been thoroughly studied over the last 25 years. Moreover, its adaptive variants from the last decade show promising results in various problem domains, and that is why the DE was selected as the author's research focus. Particularly, the dissertation is focused on the DE algorithm and its adaptive variants for small–scale continuous single–objective optimization problems with a possible expansion to the area of large–scale optimization.

2 DISSERTATION GOAL

The prevailing trend in the metaheuristic optimization seems to be a constant development of new techniques without proper justification of their need. This was nicely described by Sörensen in [6]. A similar issue is a vast amount of new versions of existing successful algorithms. In author's opinion, the main problem is not the great volume of variants, but the lack of proper analysis of implemented changes and their influence on the algorithm's behavior. Therefore, the goal of this dissertation is to try and contribute to the scientific area of metaheuristic optimization by developing analysis tools which use datamining techniques to help with understanding the population dynamic of metaheuristic algorithms. More specifically, how the control parameter adaptation in DE–based algorithms influences the population dynamic and whether this information can be used in the development and testing of new ideas.

Selected methods to achieve the above stated dissertation goal:

- **Analysis** – current state–of–the–art methods in adaptive DE field will be analyzed from the perspective of control parameter adaptation.
- **Programming** – selected state–of–the–art adaptive DE variants will be programmed in Java, Wolfram Mathematica, and Python in order to work with these algorithms and test the proposed modifications.
- **Testing** – the programmed code will be tested against possible errors and malfunctions.
- **Benchmarking** – proposed algorithm variants will be benchmarked on the basis of CEC benchmark sets of test functions.
- **Result evaluation** – evaluation of the results will be executed within the rules of used benchmark sets.
- **Result analysis** – the statistical analysis of obtained results will be performed. Population dynamic analysis will be used to asses the exploration/exploitation properties of the proposed frameworks.

3 DIFFERENTIAL EVOLUTION AND ADAPTIVITY

Troublesome fine–tuning of control parameters soon became a problem for researchers and practitioners who were trying to accommodate DE for solving complex optimization problems. Therefore, researchers started working on this problem by studying DE's behavior on different types of objective function landscapes and tried to come up with a simple guide for the setting of control parameter values e.g. [5, 7, 8].

The suggestions from different authors vary and are highly dependent on the choice of objective function testbed used in their study. This fact only supports the NFL theorem [4], which roughly states that there is no universal algorithm or algorithm parameter setting, that would solve all the different types of optimization problems optimally.

The solution to these problems may lie in the adaptive behavior of the DE algorithm. Since the setting of control parameters and mutation and crossover operators is dependent on the optimized objective function, these variables might be set during the optimization run according to the success of the currently implemented settings. There are a plethora of different variants of adaptive DEs [9], and the question is, how to select a suitable algorithm for the problem at hand. Luckily, since 2005, an annual competition in numerical optimization is held within the Congress on Evolutionary Computation (CEC), which provides a benchmark incorporating multiple test functions from various domains. These benchmarks provide a good testbed for researchers who can easily compare their algorithms with the community. Practitioners can also use the competition results as useful guidance when searching for a suitable algorithm for their problem.

Since 2013, SHADE [10] and L–SHADE [11] are core parts of the best performing algorithms of the CEC competitions [12, 13, 14, 15, 16] and form an excellent basis to start on when designing an efficient optimization algorithm for single–objective bound–constrained numerical optimization. Therefore, their selection as a starting point for the author's research in 2015 was continually justified.

4 PROPOSED METHODS

This section provides a detailed description of proposed analysis tools and adaptive frameworks for adaptive DE–based algorithms.

4.1 Population dynamic analysis

The main disadvantage of modern adaptive DE algorithms lies in their susceptibility to fast convergence towards local optima. In such a case, the algorithm loses its ability to explore the search space and aims only at the exploitation of the currently most promising area. On the other hand, algorithms that mainly explore are deemed to fail on complex and rugged objective function landscapes. Therefore, researcher's frequent goal is to find the optimal balance between their algorithm's exploration and exploitation abilities. The author believes that the exploration/exploitation abilities can be analyzed through studying the population dynamic over generations and thus, a new tool for that purpose was developed.
In order to study the speed of population convergence towards the same point in the search space (part of exploitation), the clustering of the population members was proposed. This technique is based on the Density Based Spatial Clustering of Applications with Noise algorithm (DBSCAN) [17] and is further described in section 4.1.1. For the purpose of studying the population exploration abilities, the population diversity metric can be used and is described in section 4.1.2 [18].

4.1.1 Cluster analysis

The complete description of the DBSCAN algorithm is available in the original paper [17], this section provides only its implementation for cluster analysis.

Recommended DBSCAN parameter setting:

1. Set of points S – Individuals in one population form a set of points for clustering analysis. Each point p is given by parameter values of an individual.

2. Eps = 1% of the parameter space – e.g., for the CEC2015 benchmark set with bounds $\{-100, 100\}^D$, $Eps = 2$,

3. $MinPts = 4$ (minimal number of individuals for mutation for most common DE schemes),

4. Chebyshev distance [19] – if the distance between any corresponding parameters of two individuals is higher than 1% of the parameter space, they are not considered as being in the *Eps*–neighborhood, therefore, cannot be part of the same cluster.

Clustering analysis is used to evaluate algorithms transition from exploration (ideally no clusters) to exploitation phase (clusters occur). In order to evaluate that, the DBSCAN algorithm is run on each generation of the population during the optimization run and the number of clusters and the index of generation of their first occurrence is recorded. This gives a metric, which was titled Mean Cluster Occurrence (MCO) [20]. This metric represents the average index of generation in which clusters occurred over all algorithm runs on given optimized function.
An example of cluster occurrence is shown in Fig. 4.1, where it can be seen that the Db_SHADE algorithm maintains the exploration phase longer and that clusters occur later than in the original SHADE algorithm. The figure shows mean cluster occurrence by the bold line with confidence interval pictured by the same color with lighter shade.

4.1.2 Population diversity

In order to evaluate the population's exploration ability, a population diversity metric can be used. The combination of population diversity with cluster occurrence can give a clear picture of the state in which the population resides in each generation. When comparing DE–based algorithms, higher population

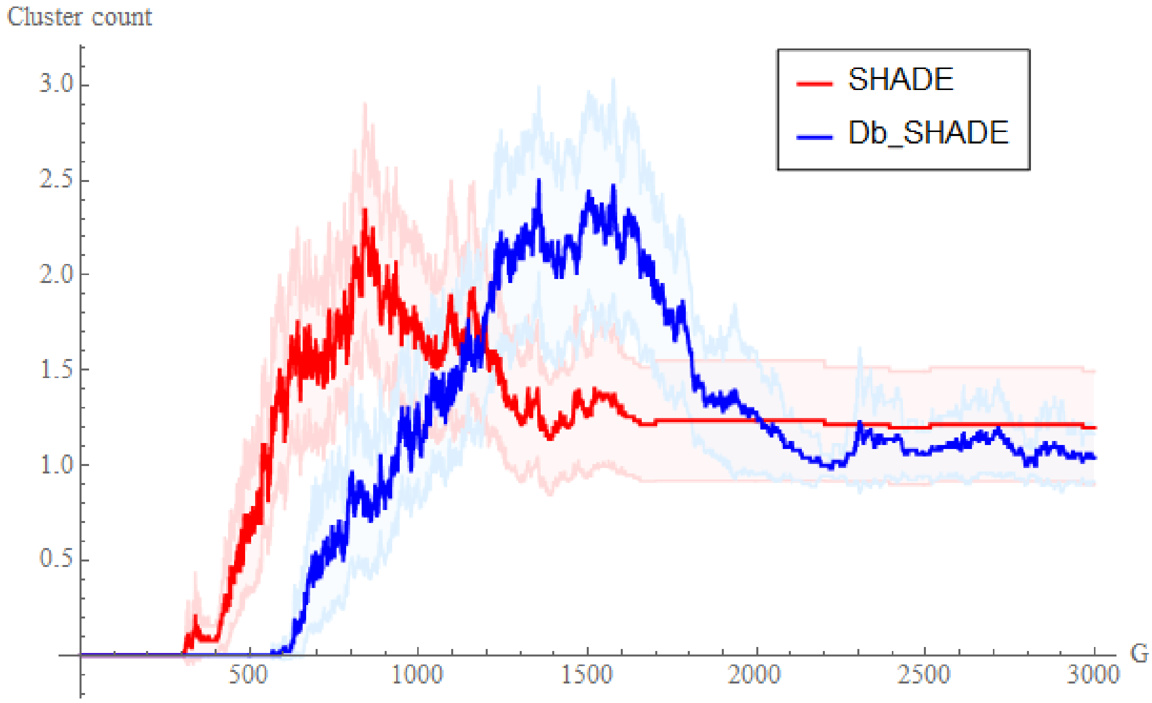

Fig. 4.1 Example of cluster occurrence comparison between SHADE and Db_SHADE algorithms on CEC 2015 benchmark, function 8, 30D.

diversity in the time of first cluster occurrence suggests that the algorithm can still escape the local optima and explore the search space further. This is also true for many other metaheuristics, not only for the DE.

An useful population diversity (*PD*) metric was proposed in [18]. This metric is based on the square root of the sum of deviations (4.2) of an individual's components from their corresponding means (4.1).

$$\overline{\boldsymbol{x}_j} = \frac{1}{NP} \sum_{i=1}^{NP} \boldsymbol{x}_{j,i} \tag{4.1}$$

$$PD = \sqrt{\frac{1}{NP} \sum_{i=1}^{NP} \sum_{j=1}^{D} (\boldsymbol{x}_{j,i} - \overline{\boldsymbol{x}_j})^2} \tag{4.2}$$

Where i is the population member iterator and j is the component (dimension) iterator.

Mean Population Diversity (MPD) [20] is a proposed metric for computing the average population diversity over multiple optimization runs in the moment of the first cluster occurrence. This metric reflects the population's potential to explore the search space after its part exploits a locally promising area.

4.2 Multi–chaotic framework for parent selection

The Multi–Chaotic (MC) framework is based on the idea of using chaotic maps as Pseudo-Random Number Generators (PRNGs) [21]; these generators are used for parent selection with a probability based on their success in generating better offspring in previous generations. The next subsections describe the framework and its use along with experimental results.

4.2.1 Chaotic maps as PRNGs

Chaotic systems implemented in this framework, with their generating equations, control parameter values, and initial position generator settings based on [22], are depicted in Tab. 4.1.

Tab. 4.1 Chaotic maps, generating equations, control parameters and initial position ranges.

Chaotic maps	Equations	Parameters	Initial position
Burgers	$X_{n+1} = aX_n - Y_n^2$ $Y_{n+1} = bY_n + X_nY_n$	$a = 0.75$ $b = 1.75$	$X_0 = U[-0.1, -0.01]$ $Y_0 = U[0.01, 0.1]$
Delayed Logistic	$X_{n+1} = AX_n(1 - Y_n)$ $Y_{n+1} = X_n$	$A = 2.27$	$X_0 = Y_0 = U[0.8, 0.9]$
Dissipative	$X_{n+1} = X_n + Y_{n+1}(\text{mod}2\pi)$ $Y_{n+1} = bY_n + k\sin X_nY_n(\text{mod}2\pi)$	$b = 0.1$ $k = 8.$	$X_0 = Y_0 = U[0, 0.1]$
Lozi	$X_{n+1} = 1 - a\lvert X_n\rvert - bY_n$ $Y_{n+1} = X_n$	$a = 1.7$ $b = 0.5$	$X_0 = Y_0 = U[0, 0.1]$
Tinkerbell	$X_{n+1} = X_n + Y_n + aX_n + bY_n$ $Y_{n+1} = 2X_nY_n + cX_n + dY_n$	$a = 0.9$ $b = -0.6$ $c = 2$ $d = 0.5$	$X_0 = U[-0.1, -0.01]$ $Y_0 = U[0, 0.1]$

In order to use these maps as PRNGs, the transformation rule has to be developed. The process of obtaining the i-th random integer value $rndInt_i$ from the chaotic map is presented in (4.3).

$$rndInt_i = \text{round}\left(\frac{\text{abs}(X_i)}{\max(\text{abs}(X_{i\in N}))} \cdot (maxRndInt - 1)\right) + 1 \tag{4.3}$$

Where $\text{abs}(X_i)$ is the absolute value of the i-th generated X coordinate from

the chaotic sequence of length N, $\max(\text{abs}(X)i \in N))$ is a maximum value of all absolute values of generated X coordinates in chaotic sequence. The function round() is a common rounding function, and *maxRndInt* is a constant to ensure that integers will be generated in the range [1, *maxRndInt*].
Each of the chaotic map based PRNGs has different probability distribution and unique sequencing. This may be beneficial for the parent selection process.

4.2.2 Parent selection

MC framework for the parent selection process is based on the ranking selection of chaotic map based PRNGs. A list of chaotic PRNGs *Clist* has to be added to the algorithm and each chaotic PRNG is initialized with the same probability $pc_{init} = 1/Csize$, where *Csize* is the size of *Clist*. For example, for five chaotic PRNGs $Csize = 5$ and each of them will have the probability of selection $pc_{init} = 1/5 = 0.2 = 20\%$.
For each target vector $\boldsymbol{x}_{i,G}$ in generation G, the chaotic generator $PRNG_k$ is selected from the *Clist* according to its probability $\boldsymbol{pc}_k$, where k is the index of selected chaotic PRNG. This selected generator is then used to replace standard PRNG for the selection of parent vectors, and if the generated trial vector succeeds in the selection, the probabilities are adjusted. There is an upper boundary for the probability of selection $pc_{max} = 0.6 = 60\%$; if the selected chaotic PRNG reaches this probability, then no adjustment takes place. The whole process is depicted in (4.4).

$$\begin{array}{ll} \text{if } f\left(\boldsymbol{u}_{i,G}\right) \leq f\left(\boldsymbol{x}_{i,G}\right) \text{ and } \boldsymbol{pc}_k < pc_{max} & \boldsymbol{pc}_j = \begin{cases} \frac{\boldsymbol{pc}_j + 0.01}{1.01} & \text{if } j = k \\ \\ \frac{\boldsymbol{pc}_j}{1.01} & \text{otherwise} \end{cases} \\ \text{otherwise} & \boldsymbol{pc}_j = \boldsymbol{pc}_j \end{array} \tag{4.4}$$

4.2.3 Results

The MC–SHADE algorithm (SHADE with Multi-Chaotic framework) was sent for the CEC 2016 competition and ranked 5$^{\text{th}}$ out of 9 contestants – Tab. 4.2. The biggest strength of the algorithm was solving optimization problems in higher dimensions – 50D and 100D.

Tab. 4.2 CEC 2016 competition ranking.

Algorithm	$D = 10$	$D = 30$	$D = 50$	$D = 100$	**Score**	**Rank**
LSHADE_EpSin	1.51E+03	3.18E+03	5.88E+03	3.33E+04	4.38E+04	1
UMOEAII	1.44E+03	4.38E+03	1.59E+04	2.96E+04	5.14E+04	2
SSEABC	2.11E+03	7.68E+03	1.91E+04	3.06E+04	5.96E+04	3
iL–SHADE	1.98E+03	5.32E+03	1.80E+04	2.23E+05	2.49E+05	4
MC–SHADE	1.96E+03	1.06E+04	4.55E+04	1.96E+05	2.54E+05	**5**
AEPDJADE	2.17E+03	8.36E+03	4.42E+04	2.77E+05	3.32E+05	6
LSHADE44	1.91E+03	5.97E+03	2.20E+04	3.76E+05	4.06E+05	7
SHADE4	1.83E+03	1.77E+04	1.65E+05	7.79E+05	9.64E+05	8
SPMGTLO	8.64E+04	2.28E+06	3.87E+07	1.10E+08	1.51E+08	9

4.3 Distance based parameter adaptation

The distance based (Db) parameter adaptation was developed for SHADE–based [10] algorithms to overcome their problem with premature convergence to local optima. The original adaptation mechanism for scaling factor F and crossover rate CR values uses weighted forms of means, where weights are based on the improvement in objective function value. Such an approach promotes exploitation over exploration, and therefore, leads to premature convergence. This is a problem, especially when solving problems of higher dimensionality. The Db approach is based on the Euclidean distance between the trial and the target individual. Scaling factor F and crossover rate CR values connected with the individual that moved the furthest will have the highest weight (4.5).

$$\boldsymbol{w}_n = \frac{\sqrt{\sum_{j=1}^{D} \left(\boldsymbol{u}_{n,j,G} - \boldsymbol{x}_{n,j,G}\right)^2}}{\sum_{m=1}^{|\boldsymbol{S}_{CR}|} \sqrt{\sum_{j=1}^{D} \left(\boldsymbol{u}_{m,j,G} - \boldsymbol{x}_{m,j,G}\right)^2}} \tag{4.5}$$

The exploration ability is rewarded, leading to avoidance of premature convergence in higher dimensional objective spaces. Such an approach might also be useful for constrained problems, where constrained areas could be overcome by individual's increased movement in the search space.

4.3.1 Results

The proposed distance based parameter adaptation was implemented into SHADE [10] and L–SHADE [11] algorithms, and the resulting algorithm variants were named Db_SHADE and DbL_SHADE respectively. Results are presented in Table 4.3.

Tab. 4.3 Wilcoxon rank-sum results in a form of wins/ties/loses from the perspective of Db adaptation enhanced algorithm - CEC 2015.

D	SHADE	L-SHADE
10	0/15/0	1/13/1
30	5/10/0	5/9/1
50	6/7/2	9/5/1
100	5/9/1	5/8/2
sum	16/41/3	20/35/5

The results show that the Db adaptation is beneficial for SHADE [10] and L–SHADE [11] algorithms when solving problems of higher dimensionality.

4.3.2 Clustering analysis

The population's clustering occurs later for the algorithm variants with Db adaptation. This is mainly true for higher dimensional settings (30, 50, and 100D). Also, when numbers of cluster occurrence instances differ between Db and non-Db version, the Db version usually clusters in fewer cases. As for the population diversity, the characteristic feature is that when clusters occur in the population, diversity is similar regardless of the used adaptation scheme. It is important to note that in Db versions, clustering occurs later. Therefore, the population can explore the search space for a longer time, which proves to be beneficial for multimodal and complex objective function landscapes.

4.4 DISH

The path to the DISH algorithm led through several successful adaptive DE algorithms - JADE [23], L-SHADE [11], iL–SHADE [24] and jSO [14]. The DISH algorithm is an implementation of distance based parameter adaptation into jSO [14] and was published in 2019 [25]. The algorithmic details are described in the dissertation, but are omitted in this work.

4.4.1 Results

The results of DISH vs. jSO on CEC 2015 and CEC 2017 benchmarks are presented in Table 4.4. Once again, it is perceivable from the results that distance based parameter adaptation is beneficial for higher dimensional problems and the algorithm variant implementing it (DISH) is able to outperform the original algorithm without it (jSO).
As it was stated in the previous chapter 4.3, the mean cluster occurrence for the algorithm variant with distance based parameter adaptation (DISH in this case) is mostly higher, therefore clusters emerge later in the optimization phase and the mean population diversity is similar during that time. This supports the initial idea of prolonging the exploration phase of the algorithm.

In order to present the algorithm to the scientific community, DISH algorithm was submitted for the CEC 2019 competition – 100–Digit Challenge [26]. The results are presented in Tab. 4.5. There were two variants in the competition – DISHchain 1e+12 by Zamuda [27] and DISH by Viktorin et al. [25]. The difference between these versions was in the larger initial population and more computing resources in the case of DISHchain 1e+12. It was shown, that the DISH algorithm is capable of obtaining competitive results and ended on joined 1$^{\text{st}}$ (DISHchain 1e+12) and 7$^{\text{th}}$ place out of 18 contestants.

Tab. 4.4 Wilcoxon rank-sum results in a form of wins/ties/loses from the perspective of DISH - CEC 2015 and CEC 2017.

D	CEC 2015	CEC 2017
10	0/15/0	0/29/1
30	3/12/0	3/26/1
50	7/8/0	14/16/0
100	6/7/2	19/10/1
sum	16/42/2	36/81/3

*Tab. 4.5 CEC 2019 competition ranking [28]. *results presented after the original deadline of the competition*

Algorithm	**Total Score**	**Ranking**
jDE100	100.00	1
DISHchain 1e+12	97.12 *(100.00)	1
HyDE–DF	93.00	2
SOMA T3A	93.00	2
ESHADE–USM	85.52	3
SOMA Pareto	85.04	4
rCIPDE	85.00	5
Co–Op	84.56	6
DISH	83.92	7
rjDE	83.52	8
mL–SHADE	78.20	9
GADE	75.44	10
CMEAL	73.44	11
HTPC	73.36	12
UMDE–MS	70.40	13
DLABC	67.88	14
MiLSHADE–LSP	60.72	15
ESP–SOMA	51.92	16

5 THE CONTRIBUTION TO SCIENCE AND PRACTICE

Author believes that one of the most important aspects of developing new heuristic optimization techniques is a proper analysis of their behaviour and identification of problem domains in which the algorithm performs adequately. Therefore, the population dynamic analysis might be a helpful tool for researchers, and can determine some of the key features of their evolutionary algorithms – described in the next section 5.1. The section 5.2 describes implementation possibilities of the proposed distance based parameter adaptation and section 5.3 is devoted to an example of practical application of DISH–based algorithm on the problem of sustainable waste–to–energy facility location.

5.1 Population dynamic analysis

The main advantages of using proposed clustering and population diversity analysis can be summarized as follows:

- **Optimization phase detection** – by combining the information from cluster and diversity analysis with additional information from the algorithm, the exploration, stall, and convergence phases can be detected.
- **Premature convergence detection** – forming of early clusters in the population is a good pointer towards premature convergence.
- **Sub–optimal computational budget** – when clusters are not formed during the whole optimization run and the population is still evolving, it is a good sign of underestimated computational budget. On the other hand, when clusters are formed, and the population diversity remains the same, it suggests an overestimated computational budget because the algorithm is most likely not going to converge any further.
- **Population size advisor** – forming of clusters that leave out only a couple of individuals might call for a larger population size. However,

forming of one large cluster suggests that there are more individuals in the same area than needed.

- **Population management tool** – when managing the population size during the optimization run, clustering information can be used to select potential candidates for removal and refine the area of new individual generation.

5.2 Distance based parameter adaptation

Distance based parameter adaptation mechanism can be implemented into various evolutionary algorithms that use a greedy approach for any weighted parameter adaptation. Thus, it may be a tool for achieving a longer exploration phase in environments suitable for it. However, it is important to consider the additional computational complexity when implementing distance based parameter adaptation. Especially the large-scale optimization and the use of Euclidean distance, may suffer from the curse of dimensionality [29].

5.3 Practical applications of DISH

DISH algorithm can be used for any optimization task with continuous parameters and can be considered a good choice for problems, which have over 30 optimized parameters since it works best with problems of higher dimensionality. One of the real–world applications is described in the next section.

5.3.1 Sustainable waste–to–energy facility location

The problem of waste–to–energy facility location with reduced energy sales and unutilized capacity of plants [30, 31] leads to a mixed–integer non–linear model, which can be solved quite efficiently for small and medium–sized instances by traditional commercial solvers. However, for larger instances, the computational complexity becomes an issue. In order to use the DISH algorithm for solving mixed–integer non–linear problems, the algorithm had to be slightly adapted and led to the emergence of the Distance Random DISH (DR_DISH) algorithm. DR_DISH algorithm combines DISH with distance–based clustering–inspired allocation of waste producers to waste–to–energy facilities with a random sequence of producer processing and can be described in a three–step process [32]:

1. **Location** – DISH algorithm determines whether or not to build a facility in each potential location (dimension of the problem is based on the number of potential new facilities, and each optimized parameter is simplified to a binary decision 1 = build, 0 = do not build).
2. Repeat N–times
   (a) **Allocation** - Randomly iterate through producers and assign them to the nearest existing facility (determined in the first step). If the nearest facility does not have enough capacity (maximum capacity is lower than the sum of waste would be), the next nearest facility with adequate capacity is selected.
   (b) **Capacities** - for each waste–to–energy facility a closest larger capacity than the sum of its waste is selected.
   (c) Evaluation of the solution quality.
3. Out of N solutions, the best is selected and returned.

The DR_DISH algorithm was tested on 14 test cases dealing with instances of the problem from the smallest (only one considered region) to the largest (all 14 regions of the Czech Republic). The results are provided in Table 5.1, where the conventional solver DICOPT [33] is incorporated as a baseline. An example of the proposed solution by DR_DISH algorithm for the whole Czech Republic is shown in Figure 5.1.

As can be seen in Table 5.1, DICOPT solver was able to provide better results up to 9 regions. However, the computational complexity became too high

Tab. 5.1 DICOPT and DR_DISH solving the sustainable waste–to–energy facility location.

# of regions [–]	Cost [M€]		# of facilities [–]		Computational time [h:mm:ss]	
	DICOPT	DR_DISH	DICOPT	DR_DISH	DICOPT	DR_DISH
1	21.0	21.0	1	1	0:00:04	0:01:48
2	46.3	47.3	5	2	0:00:15	0:03:38
3	61.6	70.0	4	4	0:00:28	0:05:31
4	94.5	102.4	9	4	0:01:15	0:08:22
5	105.5	111.5	6	4	0:01:39	0:09:46
6	119.7	127.2	10	5	0:10:09	0:12:50
7	138.5	146.3	10	5	0:02:14	0:14:54
8	159.8	162.1	12	6	3:55:32	0:17:09
9	211.0	211.9	14	8	5:54:08	0:22:21
10	–	241.9	–	9	–	0:23:44
11	–	252.3	–	10	–	0:26:19
12	–	268	–	11	–	0:31:58
13	–	292.4	–	12	–	0:38:01
14	–	301.7	–	12	–	0:40:53

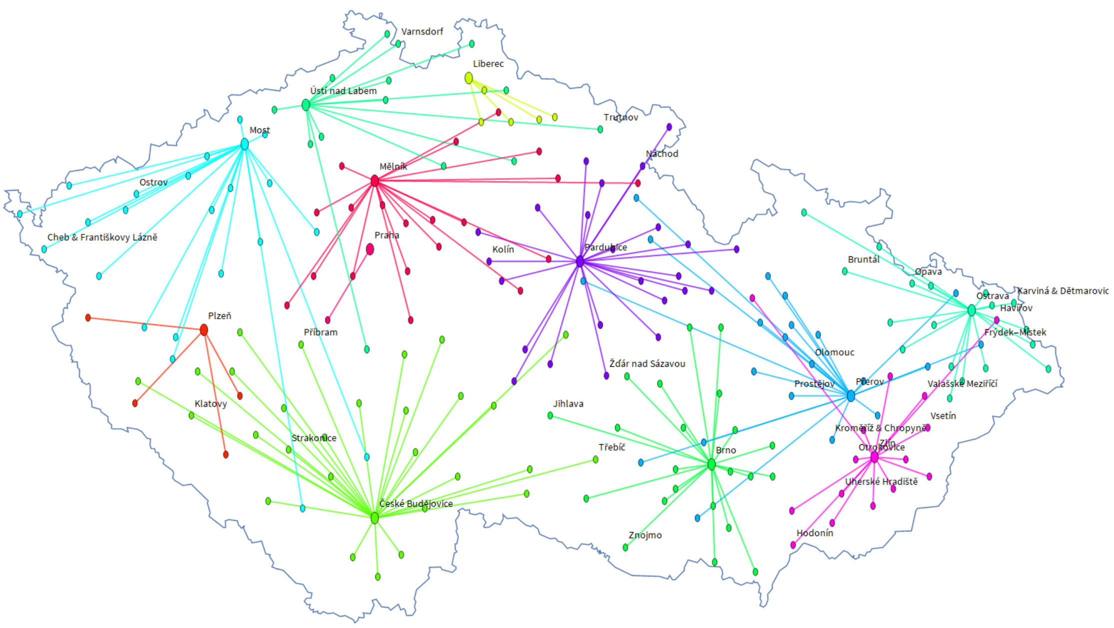

Fig. 5.1 DR_DISH solution for the sustainable waste–to–energy facility location - 14 regions.

for 10 and more regions, and the commercial solver was unable to provide a feasible solution under given experimental conditions. It is also apparent that DR_DISH provides solutions that use a smaller number of waste–to–energy facilities with higher capacity. This is important for the possible real–world implementation of the solution since it is easier to guarantee a sufficient waste supply for larger facilities. Therefore, their economic sustainability is easier [32]. Moreover, the perception of waste–to–energy facilities amongst the general public is still bad, even though the currently used technologies are ensuring clean incineration. Thus, the solution provided by DR_DISH algorithm is more likely to be implemented in practice.

6 DISSERTATION GOAL FULFILLMENT

This section describes steps that were taken in order to fulfill the dissertation goal. This was to investigate current trends in adaptive DE design and utilize datamining techniques to improve the understanding of the population dynamic and possibly use this information to develop more robust and performance-wise better algorithm variants.

- **State–of–the–art review** – current trends and ideas in the field of adaptive DE were studied and analyzed for possible deficiencies in the algorithm design [34, 35, 36].
- **Proposal of novel adaptive DE variants** – based on the knowledge gained from the first step, the proposed methods highlight understanding of the population dynamic by addressing the problem of premature convergence and fast clustering of the population [37, 38].
- **Comparison with state of the art methods** – proposed methods were implemented into the state–of–the–art algorithms (SHADE, L–SHADE and jSO [39, 25]) and compared with their canonical forms on CEC benchmark sets. The proposed algorithms were also participating in CEC competitions in 2016 [40] and 2019 [41].

- **Result analysis** – an analysis of the results was executed to understand the benefits and drawbacks of the proposed methods with the future aim of implementing this information back into the algorithm [20, 42].

7 CONCLUSION

Methods proposed in this work can be used in both – research and practice. Researchers might find clustering and population diversity analysis useful for better understanding of the collective behavior of their evolutionary algorithm's population. Thus, it can help with the development, implementation, and mainly evaluation of new ideas in the field of adaptive parameter control. Practitioners may use the analysis results to identify potential problems with incorrect computational budget or population size selection.

Following the findings of clustering and population diversity analysis of state-of-the-art DE algorithms, a distance based parameter adaptation was proposed. This led to the development of the DISH algorithm, which is a good choice for single–objective optimization problems in the continuous domain with a higher number of optimized parameters. The algorithm is reasonably easy to implement, and its implementation in Java is already available on Github [43]. It may also serve for researchers as a baseline for comparison of their proposed algorithms.

As for the distance based parameter adaptation scheme, it is possible to implement it into other population–based evolutionary algorithms to affect their balance between exploration and exploitation and help with the algorithm's performance aspect.

The author would like to utilize the knowledge gained in his doctoral studies and dedicate his future research time and capacity to the development of an analysis framework for continuous single–objective population–based optimization techniques. Such a framework should help analyze the behavior of an algorithm during the optimization phase and serve as a guide for the refinement of developed techniques.

The incremental development of new evolutionary algorithms is an ongoing process that gradually improves the quality of the heuristic optimization field

[44]. Therefore, in author's opinion, this type of research should be encouraged, but with a great emphasis on good research practices.

8 CURRICULUM VITAE

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REFERENCES

[1] Gropp, W. and Moré, J. Optimization Environments and the NEOS Server. Approximation Theory and Optimization, MD Buhmann and A. Iserles, eds, 1997.

[2] Cavazzuti, M. Deterministic Optimization. In *Optimization Methods.* : Springer Berlin Heidelberg, September 2012. pp. 77–102. doi: 10.1007/978-3-642-31187-1_4.

[3] Darwin, C. *On the Origin of Species by Means of Natural Selection Or the Preservation of Favoured Races in the Struggle for Life.* H. Milford; Oxford University Press, 1859.

[4] Wolpert, D. H. and Macready, W. G. No Free Lunch Theorems for Optimization. *IEEE Transactions on Evolutionary Computation.* 1997, vol. 1, no. 1, pp. 67–82.

[5] Price, K. and Storn, R. Differential Evolution-a simple and efficient adaptive scheme for global optimization over continuous space. Technical report, Technical Report, International Computer Science Institute, 1995.

[6] Sörensen, K. Metaheuristics—the metaphor exposed. *International Transactions in Operational Research.* 2015, vol. 22, no. 1, pp. 3–18. doi: https://doi.org/10.1111/itor.12001.

[7] Gämperle, R., Müller, S. D. and Koumoutsakos, P. A parameter study for differential evolution. *Advances in intelligent systems, fuzzy systems, evolutionary computation.* 2002, vol. 10, no. 10, pp. 293–298.

[8] Ronkkonen, J., Kukkonen, S. and Price, K. Real-Parameter Optimization with Differential Evolution. In *2005 IEEE Congress on Evolutionary Computation.* IEEE, 2005. doi: 10.1109/cec.2005.1554725.

[9] Das, S., Mullick, S. S. and Suganthan, P. N. Recent advances in differential evolution – An updated survey. *Swarm and Evolutionary Computation.* 2016, vol. 27, pp. 1–30.

[10] Tanabe, R. and Fukunaga, A. Success-history based parameter adaptation for Differential Evolution. In *2013 IEEE Congress on Evolutionary Computation (CEC)*, pp. 71–78. IEEE, 2013.

[11] Tanabe, R. and Fukunaga, A. S. Improving the search performance of SHADE using linear population size reduction. In *2014 IEEE Congress on Evolutionary Computation (CEC)*, pp. 1658–1665, 2014.

[12] Guo, S.-M., Tsai, J. S.-H., Yang, C.-C. and Hsu, P.-H. A self-optimization approach for L-SHADE incorporated with eigenvector-based crossover and successful-parent-selecting framework on CEC 2015 benchmark set. In *2015 IEEE congress on evolutionary computation (CEC)*, pp. 1003–1010. IEEE, 2015.

[13] Awad, N., Ali, M. Z. and Reynolds, R. G. A differential evolution algorithm with success-based parameter adaptation for CEC2015 learning-based optimization. In *2015 IEEE Congress on Evolutionary Computation (CEC)*. IEEE, May 2015. doi: 10.1109/cec.2015.7257012.

[14] Brest, J., Maučec, M. S. and Bošković, B. Single objective real-parameter optimization: algorithm jSO. In *2017 IEEE congress on evolutionary computation (CEC)*, pp. 1311–1318. IEEE, 2017.

[15] Awad, N. H., Ali, M. Z. and Suganthan, P. N. Ensemble sinusoidal differential covariance matrix adaptation with Euclidean neighborhood for solving CEC2017 benchmark problems. In *2017 IEEE Congress on Evolutionary Computation (CEC)*, pp. 372–379. IEEE, 2017.

[16] Mohamed, A. W., Hadi, A. A., Fattouh, A. M. and Jambi, K. M. LSHADE with semi-parameter adaptation hybrid with CMA-ES for solving CEC 2017 benchmark problems. In *2017 IEEE Congress on evolutionary computation (CEC)*, pp. 145–152. IEEE, 2017.

[17] Ester, M., Kriegel, H.-P., Sander, J., Xu, X. and others. A density-based algorithm for discovering clusters in large spatial databases with noise. In *Kdd*, vol. 96, pp. 226–231, 1996.

[18] Poláková, R., Tvrdík, J., Bujok, P. and Matoušek, R. Population-size adaptation through diversity-control mechanism for differential evolution. In *MENDEL, 22th International Conference on Soft Computing*, pp. 49–56, 2016.

[19] Deza, M. M. and Deza, E. Encyclopedia of Distances. In *Encyclopedia of Distances.* : Springer, 2009. pp. 1–583.

[20] Viktorin, A., Senkerik, R., Pluhacek, M. and Kadavy, T. Clustering Analysis of the Population in Db_SHADE Algorithm. *MENDEL.* Jun. 2018, vol. 24, no. 1, pp. 9–16. doi: 10.13164/mendel.2018.1.009.

[21] PLUHACEK, M. *Modern methods of development and modification of evolutionary computational techniques.* Doctoral Thesis, Tiomas Bata University in Zlín, Faculty of Applied Informatics, Zlín, 2015.

[22] Sprott, J. C. and Sprott, J. C. *Chaos and time-series analysis.* Oxford University Press, 2003. ISBN 9780198508403.

[23] Zhang, J. and Sanderson, A. C. JADE: adaptive differential evolution with optional external archive. *IEEE Transactions on evolutionary computation.* 2009, vol. 13, no. 5, pp. 945–958.

[24] Brest, J., Maučec, M. S. and Bošković, B. iL-SHADE: Improved L-SHADE Algorithm for Single Objective Real-Parameter Optimization. In *2016 IEEE World Congress on Computational Intelligence (IEEE WCCI 2016), Vancouver, Canada*, pp. 1188–1195, 2016.

[25] Viktorin, A., Senkerik, R., Pluhacek, M., Kadavy, T. and Zamuda, A. Distance based parameter adaptation for success-history based differential evolution. *Swarm and Evolutionary Computation.* 2019, vol. 50, pp. 100462.

[26] Price, K., Awad, N., Ali, M. and Suganthan, P. Problem definitions and evaluation criteria for the 100-digit challenge special session and competition on single objective numerical optimization. In *Technical Report.* : Nanyang Technological University, 2018.

[27] Zamuda, A. Function Evaluations Upto 1e+12 and Large Population Sizes Assessed in Distance-Based Success History Differential Evolution for 100-Digit Challenge and Numerical Optimization Scenarios (DISHchain 1e+12): A Competition Entry for "100-Digit Challenge, and Four Other Numerical Optimization Competitions" at the Genetic and Evolutionary Computation Conference (CECCO) 2019. In *Proceedings of the Genetic and Evolutionary Computation Conference Companion*, GECCO '19, pp. 11–12, New York, NY, USA, 2019. Association for Computing Machinery. doi: 10.1145/3319619.3326751. ISBN 9781450367486.

[28] Price, K., Awad, N., Ali, M. and Suganthan, P. The 2019 100-Digit Challenge on Real-Parameter, Single Objective Optimization: Analysis of Results. Technical report, Technical Report 2019. Available online: https:// www.ntu.edu.sg /home /epnsugan /index_files /CEC2019 /CEC2019.htm, 2019.

[29] Bellman, R. *Dynamic Programming.* Dover Books on Computer Science Series. Dover Publications, 2003. Available at: `<https://books.google.cz/books?id=fyVtp3EMxasC>`. ISBN 9780486428093.

[30] Ferdan, T., Šomplák and Pavlas, M. Improved feasibility analysis under volatile conditions: Case of waste-to-energy. *Chemical Engineering Transactions*. 2014, vol. 39, pp. 691–696. doi: 10.3303/CET1439116.

[31] Kyriakis, E., Psomopoulos, C., Kokkotis, P., Bourtsalas, A. and N., T. A step by step selection method for the location and the size of a waste-to-energy facility targeting the maximum output energy and minimization of gate fee. *Environmental Science and Pollution Research*. 2018, vol. 25, pp. 26715–26724. doi: 10.1007/s11356-017-9488-1.

[32] Hrabec, D., Šomplák, R., Nevrlý, V., Viktorin, A., Pluháček, M. and Popela, P. Sustainable waste-to-energy facility location: Influence of demand on energy sales. *Energy*. 2020, vol. 207, pp. 118257. ISSN 0360-5442. doi: https://doi.org/10.1016/j.energy.2020.118257.

[33] Grossmann, I. E., Viswanathan, J., Vecchietti, A., Raman, R., Kalvelagen, E. and others. GAMS/DICOPT: A discrete continuous optimization package. *GAMS Corporation Inc.* 2002, vol. 37, pp. 55.

[34] Viktorin, A., Senkerik, R., Pluhacek, M. and Kadavy, T. The Influence of Archive Size to SHADE. In Silhavy, R., Senkerik, R., Kominkova Oplatkova, Z., Prokopova, Z. and Silhavy, P. (Ed.) *Artificial Intelligence Trends in Intelligent Systems*, pp. 517–527, Cham, 2017. Springer International Publishing. ISBN 978-3-319-57261-1.

[35] Viktorin, A., Pluhacek, M., Senkerik, R. and Kadavy, T. Detecting Potential Design Weaknesses in SHADE Through Network Feature Analysis. In Pisón, F. J., Urraca, R., Quintián, H. and Corchado, E. (Ed.) *Hybrid Artificial Intelligent Systems*, pp. 662–673, Cham, 2017. Springer International Publishing. ISBN 978-3-319-59650-1.

[36] Viktorin, A., Senkerik, R., Pluhacek, M. and Kadavy, T. Analysing knowledge transfer in SHADE via complex network. *Logic Journal of the IGPL*. 09 2018, vol. 28, no. 2, pp. 153–170. ISSN 1367-0751. doi: 10.1093/jigpal/jzy042.

[37] Viktorin, A., Pluhacek, M. and Senkerik, R. Success-history based adaptive differential evolution algorithm with multi-chaotic framework for parent selection performance on CEC2014 benchmark set. In *2016 IEEE Congress on Evolutionary Computation (CEC)*. IEEE, July 2016. doi: 10.1109/cec.2016.7744404.

[38] Viktorin, A., Senkerik, R., Pluhacek, M., Kadavy, T. and Zamuda, A. Distance based parameter adaptation for differential evolution. In *2017 IEEE Symposium Series on Computational Intelligence (SSCI)*. IEEE, November 2017. doi: 10.1109/ssci.2017.8280959.

[39] Viktorin, A., Senkerik, R., Pluhacek, M., Kadavy, T. and Zamuda, A. Distance based parameter adaptation for differential evolution. In *2017 IEEE Symposium Series on Computational Intelligence (SSCI)*, pp. 1–7. IEEE, 2017.

[40] Liang, J., Qu, B. and Suganthan, P. Problem definitions and evaluation criteria for the CEC 2014 special session and competition on single objective real-parameter numerical optimization. *Computational Intelligence Laboratory, Zhengzhou University, Zhengzhou China and Technical Report, Nanyang Technological University, Singapore*. 2013, vol. 635.

[41] Price, K., Awad, N., Ali, M. and Suganthan, P. Problem definitions and evaluation criteria for the 100-digit challenge special session and competition on single objective numerical optimization. In *Technical Report*. : Nanyang Technological University, 2018.

[42] Viktorin, A., Senkerik, R., Pluhacek, M. and Kadavy, T. Analyzing Control Parameters in DISH. In Rutkowski, L., Scherer, R., Korytkowski, M., Pedrycz, W., Tadeusiewicz, R. and Zurada, J. M. (Ed.) *Artificial Intelligence and Soft Computing*, pp. 519–529, Cham, 2019. Springer International Publishing. ISBN 978-3-030-20912-4.

[43] Viktorin, A. *TBU–AILab: DISH_java*, 2020. Available at: `<https://github.com/TBU-AILab/DISH_java>`.

[44] Piotrowski, A. P. and Napiorkowski, J. J. Step-by-step improvement of JADE and SHADE-based algorithms: Success or failure? *Swarm and Evolutionary Computation*. 2018, vol. 43, pp. 88 – 108. ISSN 2210-6502. doi: https://doi.org/10.1016/j.swevo.2018.03.007.

PUBLICATIONS OF THE AUTHOR

Journals with IF

[1] VIKTORIN, Adam, SENKERIK, Roman, PLUHACEK, Michal, KADAVY, Tomas, ZAMUDA, Ales. Distance based parameter adaptation for Success-History based Differential Evolution. Swarm and Evolutionary Computation, 2019, 2019, vol. 50, pp. 1-17. ISSN 2210-6502.

[2] VIKTORIN, Adam, SENKERIK, Roman, PLUHACEK, Michal, KADAVY, Tomas. Analysing knowledge transfer in SHADE via complex network. LOGIC JOURNAL OF THE IGPL, 2020, vol. 28, no. 2, pp. 153-170. ISSN 1367-0751.

[3] HRABEC, Dusan, SOMPLAK, Radovan, NEVRLY, Vlastimir, VIKTORIN, Adam, PLUHACEK, Michal, POPELA, Pavel. Sustainable waste-to-energy facility location: Influence of demand on energy sales. Energy, 2020, vol. 207, pp. 1-15. ISSN 0360-5442.

[4] PLUHACEK, Michal, VIKTORIN, Adam, SENKERIK, Roman, KADAVY, Tomas, ZELINKA, Ivan. Extended experimental study on PSO with partial population restart based on complex network analysis. LOGIC JOURNAL OF THE IGPL, 2020, vol. 28, no. 2, pp. 211-225. ISSN 1367-0751.

Journals in Scopus

[5] VIKTORIN, Adam, SENKERIK, Roman, PLUHACEK, Michal, KADAVY, Tomas. Modified progressive random walk with chaotic PRNG. International Journal of Parallel, Emergent and Distributed Systems, 2017, pp. 1-10. ISSN 1744-5760.

[6] VIKTORIN, Adam, SENKERIK, Roman, PLUHACEK, Michal, KADAVY, Tomas. Clustering analysis of the population in Db_SHADE algorithm. Mendel, 2018, vol. 24, no. 1, pp. 9-16. ISSN 1803-3814.

[7] SENKERIK, Roman, VIKTORIN, Adam, ZELINKA, Ivan, PLUHACEK, Michal, KADAVY, Tomas, KOMINKOVA OPLATKOVA, Zuzana, BHATEJA, Vikrant, CHANDRA SATAPATHY, Suresh. Differential Evolution And Deterministic Chaotic Series: A Detailed Study. Mendel, 2018, vol. 24, no. 2, pp. 61-68. ISSN 1803-3814.

[8] PLUHACEK, Michal, ZELINKA, Ivan, SENKERIK, Roman, VIKTORIN, Adam, KADAVY, Tomas. Particle swarm optimization with distance based repulsivity. Mendel, 2018, 2018, vol. 24, no. 2, pp. 81-86. ISSN 1803-3814.

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CEC	Congress on Evolutionary Computation
CR	Crossover rate
D	Dimension
Db	Distance based parameter adaptation
DBSCAN	Density Based Spatial Clustering of Applications with Noise
DE	Differential Evolution
DISH	Distance based parameter adaptation for Success–History based DE
DR_DISH	Distance Random DISH
ECT	Evolutionary Computation Technique
F	Scaling factor
iL–SHADE	Improved L–SHADE
L-SHADE	SHADE with Linear decrease of the population size
MCO	Mean Cluster Occurrence
MC–SHADE	SHADE with Multi–Chaotic parent selection framework
MPD	Mean Population Diversity
NFL	No Free Lunch theorem
NP	Population size
PD	Population Diversity
PRNG	Pseudo–Random Number Generator
SHADE	Success–History based Adaptive DE

Adaptace kontrolních parametrů v diferenciální evoluci

Control Parameter Adaptation in Differential Evolution

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