# On the Performance of Evolutionary Algorithms in Biomedical Keyword Clustering

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## ABSTRACT

In the field of life sciences it often turns out to be a challenge to quickly find the desired information due to the huge amount of available data. The research area of information retrieval (IR) addresses this problem and tries to provide suitable solutions. One of the approaches used in IR is query extension based on keyword or document clusters.

In this paper we present a deep analysis of a keyword clustering approach using four different kinds of evolutionary algorithms, namely evolution strategy (ES), genetic algorithm (GA), genetic algorithm with strict offspring selection (OSGA), and the multi-objective elitist non-dominated sorting genetic algorithm (NSGA-II).

We have identified features that characterize solution candidates for the keyword clustering problem, e.g., the number of documents covered and how well the identified clusters of keywords match with the occurrence of keywords in the given set of documents. The use of these features and how evolutionary algorithms can be used to solve the optimization of keyword clusters is shown in this paper.

To test the here presented approach we used a real world data set provided within the TREC-9 conference; this data collection includes information about approximately 36,000 documents collected from the PubMed database.

In the results section we compare the performance of the here tested evolutionary algorithms and see that especially ES and NSGA-II produce meaningful results for this documents collection. This approach based on evolutionary algorithms shall be used further on in automated query extension for biomedical information retrieval in PubMed.

## Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Heuristic methods; I.7.5 [**Document and Text Processing**]: Document Capture; J.3 [**Life and Medical Sciences**]: Medical Information Systems

## General Terms

Algorithms, Experimentation, Theory

## Keywords

Information Retrieval, Bioinformatics, Evolutionary Algorithms, Keyword Clustering, Query Extension

## 1. INTRODUCTION AND MOTIVATION

Information retrieval in the field of life sciences gains more and more importance due to the nearly exponentially growing amount of available data. To obtain the information searched for in a reasonable amount of time good search algorithms are needed. Query extension is one of these methods and is well-known in biomedical information retrieval [5]: Queries of users are extended by suitable words to find more significant results. To be able to extend these search strings by first identifying matching keywords, good keyword clusters or document clusters are required. In [3] we have already proposed a new keyword clustering method with evolutionary algorithms. In this paper we provide a deeper analysis of the use of various methods with our keyword clustering approach.


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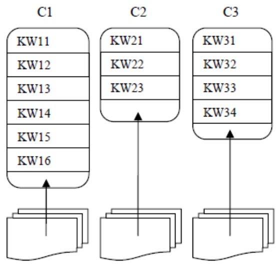


**Figure 1: Example of a keyword clustering solution candidate taken from [3].**

## 1.1 Solution Candidate Structure

A keyword clustering solution candidate $c$ consists of $|c|$ clusters; each cluster $c_i$ contains $n_i$ keywords. Each document $d$ comprises $|KW(d)|$ keywords. Documents are assigned to clusters through their keywords, i.e., if a cluster $c_i$ contains a keyword $k_j$ and a document $d_l$ contains the same keyword, then $d_l$ is assigned to $c_i$. In Figure 1 we provide a schematic view of a solution candidate. We have implemented various genetic operators for mutating and crossing the described solution candidates that can be used in evolutionary algorithms for keyword cluster optimization. Details on these operators can be found in [3].

## 1.2 Fitness Function

To be able to evaluate a generated solution candidate an appropriate fitness function is needed. The function proposed here does not rely on the often used distances of words in the cluster [4], but takes into account some properties we consider essential for a keyword cluster. The combination of these properties and respective weighting factors conclude the fitness function.

### *1.2.1 Parameters*

The following features, also previously described in [3], have been identified to be important in keyword cluster optimization:

$$A = 1 - \left(\frac{At}{Ad} - 1\right) \tag{1}$$

$$B = \frac{Ad}{N} \tag{2}$$

$$cConf(C_i) = \frac{\sum_{d \in d_{C_i}} \frac{|KW : KW \in KW(d) \,\&\, KW \in C_i|}{|KW(d)|}}{|d_{C_i}|} \tag{3}$$

$$C = \frac{\sum_{i=1}^{CK} cConf(C_i)}{CK} \tag{4}$$

$$dConf(d_j, C_i) = \frac{|KW : KW \in KW_j \,\&\, KW \in C_i|}{|KW(C_i)|} \tag{5}$$

$$D = \frac{\sum_{i=1}^{CK} \left(\frac{\sum_{d_j \in d_{C_i}} dConf(d_j, C_i)}{|d_{C_i}|}\right)}{CK} \tag{6}$$

$$E = 1 - \sqrt{\frac{1}{CK - 1} \sum_{i=1}^{CK} (N_{C_i} - \overline{N_C})^2} \tag{7}$$

$$G = 1 - \left(\frac{|CK - \varphi * \log N|}{\varphi * \log N}\right)^2 \tag{8}$$

where $Ad$ is the number of distinct documents assigned to a cluster, $At$ is the total number of assigned documents including multiple assignments, $N$ is the total number of documents, and $CK$ the number of keyword clusters. Parameter A is relevant as we are interested in assigning documents to as few clusters as possible. Parameter B quantifies the number of documents included in the clustering. In parameter C the cluster confidence of all clusters is measured; a cluster is regarded as confident if its assigned documents contain only keywords also present in the cluster. In contrast, parameter D deals with the document confidence of the documents assigned to a cluster; a document is considered as confident if the cluster it is assigned to comprises only keywords also present in the document. Parameter E provides a measurement of the standard deviation of the number of documents assigned to the clusters and parameter G deals with the number of generated clusters. Using the variable $\varphi$ in Equation 8 we define the approximate number of desired clusters.

The combination of these parameters leads to the following fitness function:

$$F = \alpha * A + \beta * B + \gamma * C + \delta * D + \epsilon * E + \zeta * G \tag{9}$$

where $A$, $B$, $C$, $D$, $E$ and $G$ are the parameters described in Equations 1 - 8 and $\alpha$, $\beta$, $\gamma$, $\delta$, $\epsilon$ and $\zeta$ are their corresponding weighting factors. Additional details on this fitness function and the contributors are given in [3].

### *1.2.2 Example*

For a better understanding we here provide an example of fitness calculation. Let us assume we have three documents $d_1$, $d_2$, and $d_3$ containing various keywords (see Table 1).

| Document $d_1$ | Document $d_2$ | Document $d_3$ |
|---|---|---|
| lung | cancer | heart |
| cancer | smoke | attack |
| alveolus | cigarette | myocardial |

**Table 1: Example: Documents**

| Cluster $C_1$ | Cluster $C_2$ | Cluster $C_3$ |
|---|---|---|
| cancer | heart | lung |
| smoke | myocardial | heart |

**Table 2: Example: Keyword clustering solution candidate**

| $C_1$ | $C_2$ | $C_3$ |
|---|---|---|
| $d_1$ | $d_3$ | $d_1$ |
| $d_2$ | | $d_3$ |

**Table 3: Example: Documents assigned to the solution candidate in Table 2**

Further, we assume our algorithm has created the keyword clustering candidate depicted in Table 2. In Table 3 we provide the assignments of the documents to the clusters. Calculating the values for the Equations 1 - 8, assuming $\varphi = 4$, we get:

$$A = 1 - \left(\frac{At}{Ad} - 1\right) = 1 - \left(\frac{5}{3} - 1\right) = \frac{1}{3}$$

$$B = \frac{Ad}{N} = \frac{3}{3} = 1$$

$$cConf(C_1) = \frac{\sum_{d \in d_{C_1}} \frac{|KW:KW \in KW(d) \,\&\, KW \in C_1|}{|KW(d)|}}{|d_{C_1}|} = $$

$$= \frac{1}{2} * \left(\frac{1}{3} + \frac{2}{3}\right) = \frac{1}{2}$$

$$cConf(C_2) = \frac{\sum_{d \in d_{C_2}} \frac{|KW:KW \in KW(d) \,\&\, KW \in C_2|}{|KW(d)|}}{|d_{C_2}|} = \frac{2}{3}$$

$$cConf(C_3) = \frac{\sum_{d \in d_{C_3}} \frac{|KW:KW \in KW(d) \,\&\, KW \in C_3|}{|KW(d)|}}{|d_{C_3}|} = \frac{1}{3}$$

$$C = \frac{\sum_{i=1}^{CK} cConf(C_i)}{CK} =$$

$$= \frac{1}{3} * \left(\sum_{i=1}^{3} cConf(C_i)\right) = \frac{1}{2}$$

$$dConf(d_1, C_1) = \frac{|KW : KW \in d_1 \,\&\, KW \in C_1|}{|KW(C_1)|} = \frac{1}{2}$$

$$dConf(d_2, C_1) = \frac{|KW : KW \in d_2 \,\&\, KW \in C_1|}{|KW(C_1)|} = \frac{2}{2} = 1$$

$$dConf(d_3, C_2) = 1$$

$$dConf(d_1, C_3) = dConf(d_3, C_3) = \frac{1}{2}$$

$$D = \frac{\sum_{i=1}^{CK} \left(\frac{\sum_{d_j \in d_{C_i}} dConf(d_j, C_i)}{|d_{C_i}|}\right)}{CK} =$$

$$= \frac{1}{3} * \left(\frac{\frac{1}{2} + 1}{2} + 1 + \frac{\frac{1}{2} + \frac{1}{2}}{2}\right) = \frac{3}{4}$$

$$E = 1 - \sqrt{\frac{1}{CK - 1} \sum_{i=1}^{CK} (N_{C_i} - \overline{N_C})^2} =$$

$$= 1 - \sqrt{\frac{1}{2}\left(\left(2 - \frac{5}{3}\right)^2 + \left(1 - \frac{5}{3}\right)^2 + \left(2 - \frac{5}{3}\right)^2\right)} \approx 0.42$$

$$G = 1 - \left(\frac{|CK - \varphi * \log N|}{\varphi * \log N}\right)^2 =$$

$$= 1 - \left(\frac{|3 - 4 * \log 3|}{4 * \log 3}\right)^2 \approx 0.67$$

With equal weighting, i.e., setting $\alpha$, $\beta$, $\gamma$, $\delta$, $\epsilon$ and $\zeta$ to 1, we obtain the following fitness value for our example:

$$F = \alpha * A + \beta * B + \gamma * C + \delta * D + \epsilon * E + \zeta * G \approx$$

$$\approx \frac{1}{3} + 1 + \frac{1}{2} + \frac{3}{4} + 0.42 + 0.67 \approx 3.67$$

An example for an optimal solution could in this case consist of 2 clusters, cluster 1 holding document $d_1$ and $d_2$ and keywords "cancer", "smoke", and "lung", and cluster 2 containing $d_3$ with all its three keywords. The fitness value of this solution would then be 4.66.

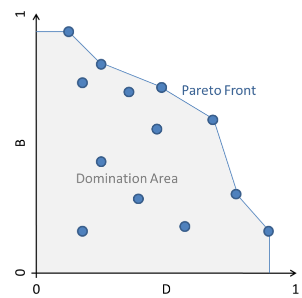


**Figure 2: Example of a Pareto front**

## 2. METHODS

We have tested our clustering approach with several evolutionary algorithms (EAs). In first tests [3] we realized that including a lot of documents in the clustering (parameter B in Equation 2) and having a high cluster and document confidence (parameter C in Equation 4 and D in Equation 6) can be contrary objectives. Therefore, we have decided not only to perform analyses with single-objective EAs but to try also a multi-objective approach. We used the open source framework HeuristicLab [10] as base for our work (`http://dev.heuristiclab.com`).

As single-objective representatives of evolutionary algorithms we use Evolution Strategy (ES) [9], Genetic Algorithms (GA) [6] and Genetic Algorithms with strict Offspring Selection (OSGA) [1]. While ES is mainly driven by mutation and selection, the evolutionary process in genetic algorithms is directed by the interplay of mutation, crossover and selection. The OSGA is an extension of the standard GA and additionally includes an offspring selection step.

Since we have in this context also contrary objectives we use also a representative of multi-objective EAs: the elitist non-dominated sorting genetic algorithm (NSGA-II) [2]. The NSGA-II generates a so-called Pareto front of solutions; these solutions are Pareto optimal, i.e., they are not dominated by any other solution as illustrated in Figure 2[1].

## 3. EMPIRICAL TESTS

### 3.1 Clustering Data

The data used for testing our approach was taken from the 9th Text Retrieval Conference (TREC-9) in the year 2000 [11] containing 36,890 entries. Each item is a PubMed [7] entry, containing title, abstract, authors, source, publication type, and its medical subject headings (MeSH) [8]. MeSH terms are a controlled vocabulary used to categorize medical issues. We chose this data set because we consider it important to evaluate new methods on real world problems.

We have preprocessed those entries by removing the so-called stop words (e.g., "a", "and", "or") and by using the $tf - idf$ weighting. This weighting is often applied in IR (as for example described in [4] and [5]) to extract the most

[1]In the context of muli-criterial optimization a solution dominates another solution if it is better or equal with respect to all defined qualities. For details please see [2].

| configuration | $\alpha$ | $\beta$ | $\gamma$ | $\delta$ | $\epsilon$ | $\zeta$ | $\phi$ |
|---|---|---|---|---|---|---|---|
| I | 0.1 | 2 | 3 | 0.3 | 0.001 | 2 | 100 |
| II | 1 | 3 | 7 | 0.5 | 0.001 | 2 | 100 |
| III | 2 | 5 | 4 | 0.5 | 0.001 | 2 | 100 |

**Table 4: Weighting factor settings for single-objective tests**

| configuration | population size | WF config | mutation rate |
|---|---|---|---|
| OSGA.1 | 10 | I | 5% |
| OSGA.2 | 10 | I | 10% |
| OSGA.3 | 10 | I | 20% |
| OSGA.4 | 10 | I | 50% |
| OSGA.5 | 10 | II | 5% |
| OSGA.6 | 10 | II | 10% |
| OSGA.7 | 10 | II | 20% |
| OSGA.8 | 10 | II | 50% |
| OSGA.9 | 10 | III | 5% |
| OSGA.10 | 10 | III | 10% |
| OSGA.11 | 10 | III | 20% |
| OSGA.12 | 10 | III | 50% |
| OSGA.13 | 50 | I | 5% |
| OSGA.14 | 50 | I | 10% |
| OSGA.15 | 50 | I | 20% |
| OSGA.16 | 50 | I | 50% |
| OSGA.17 | 50 | II | 5% |
| OSGA.18 | 50 | II | 10% |
| OSGA.19 | 50 | II | 20% |
| OSGA.20 | 50 | II | 50% |
| OSGA.21 | 50 | III | 5% |
| OSGA.22 | 50 | III | 10% |
| OSGA.23 | 50 | III | 20% |
| OSGA.24 | 50 | III | 50% |

**Table 5: Algorithm parameters for OSGA**

significant words. The formula is given by

$$d_{ij} = tf_{ij} * idf_j \tag{10}$$

where $tf_{ij}$ is the term frequency of term $j$ in document $i$ and $idf_j$ is the inverse document frequency of term $j$. If a specific word occurs very frequently in a specific document but not in all other documents, then it is considered as significant for the mentioned document and has a high $d_{ij}$ value. The threshold used here was the average frequency. Using this weighting we have eliminated a lot of non-significant words such as for example "human", which occurred in 78% of the data. All in all only 29% of the available keywords remained.

## 3.2 Test Setup

We used different population sizes (namely 10 and 50 for OSGA and NSGA-II; 50 and 200 for GA) and mutation rates (5%, 10%, 20%, and 50% for GA and OSGA; 10%, 20%, 50%, and 100% for the NSGA-II). For ES three different settings for $\mu$+$\lambda$ were used (namely 1+1, 1+10, 10+100). Three different weighting factor settings have been tested for the single-objective methods (see Table 4), for the NSGA-II we optimized parameters $B$, $C$, and $D$. The number of evaluated solutions was set to 10,000 for all algorithms and all parameter settings and for each setup 5 independent runs have been executed. See Tables 5 - 8 for more details.

## 3.3 Results

In Tables 9 - 13 the results of our empirical tests are presented. In addition to the original OSGA tests in which the maximum selection pressure was set to 100, we here also show results for the same runs for which the maximum selection pressure was set to 1,000. The average and standard deviation numbers presented here describe the quality and parameter values of the best solutions of five independent

| configuration | $\mu$ | $\lambda$ | WF config |
|---|---|---|---|
| ES.1 | 1 | 1 | I |
| ES.2 | 1 | 1 | II |
| ES.3 | 1 | 1 | III |
| ES.4 | 1 | 10 | I |
| ES.5 | 1 | 10 | II |
| ES.6 | 1 | 10 | III |
| ES.7 | 10 | 100 | I |
| ES.8 | 10 | 100 | II |
| ES.9 | 10 | 100 | III |

**Table 6: Algorithm parameters for ES**

| configuration | population size | WF config | mutation rate |
|---|---|---|---|
| GA.1 | 50 | I | 5% |
| GA.2 | 50 | I | 10% |
| GA.3 | 50 | I | 20% |
| GA.4 | 50 | I | 50% |
| GA.5 | 50 | II | 5% |
| GA.6 | 50 | II | 10% |
| GA.7 | 50 | II | 20% |
| GA.8 | 50 | II | 50% |
| GA.9 | 50 | III | 5% |
| GA.10 | 50 | III | 10% |
| GA.11 | 50 | III | 20% |
| GA.12 | 50 | III | 50% |
| GA.13 | 200 | I | 5% |
| GA.14 | 200 | I | 10% |
| GA.15 | 200 | I | 20% |
| GA.16 | 200 | I | 50% |
| GA.17 | 200 | II | 5% |
| GA.18 | 200 | II | 10% |
| GA.19 | 200 | II | 20% |
| GA.20 | 200 | II | 50% |
| GA.21 | 200 | III | 5% |
| GA.22 | 200 | III | 10% |
| GA.23 | 200 | III | 20% |
| GA.24 | 200 | III | 50% |

**Table 7: Algorithm parameters for GA**

| configuration | population size | mutation rate |
|---|---|---|
| NSGA.1 | 10 | 10% |
| NSGA.2 | 10 | 20% |
| NSGA.3 | 10 | 50% |
| NSGA.4 | 10 | 100% |
| NSGA.5 | 100 | 10% |
| NSGA.6 | 100 | 20% |
| NSGA.7 | 100 | 50% |
| NSGA.8 | 100 | 100% |

**Table 8: Algorithm parameters for NSGA-II**

| configuration | ES | GA | OSGA 100 | OSGA 1000 | NSGA-II |
|---|---|---|---|---|---|
| 1 | 00:28:31 | 65:26:30 | 00:38:00 | 01:05:10 | 07:42:57 |
| 2 | 00:17:05 | 63:48:37 | 00:33:26 | 00:48:50 | 14:24:17 |
| 3 | 00:15:41 | 70:24:20 | 00:39:02 | 00:51:10 | 08:00:49 |
| 4 | 00:07:23 | 74:40:22 | 00:39:18 | 01:01:11 | 06:00:28 |
| 5 | 00:10:06 | 00:30:11 | 00:00:59 | 00:08:46 | 138:16:52 |
| 6 | 00:09:12 | 00:39:08 | 00:01:06 | 00:05:16 | 94:49:59 |
| 7 | 00:08:30 | 00:41:30 | 00:01:21 | 00:06:16 | 46:06:23 |
| 8 | 00:05:37 | 00:51:54 | 00:01:19 | 00:10:20 | 38:51:16 |
| 9 | 00:05:34 | 00:17:45 | 00:00:50 | 00:07:30 | |
| 10 | | 00:19:14 | 00:00:58 | 00:05:11 | |
| 11 | | 00:20:32 | 00:01:03 | 00:05:11 | |
| 12 | | 00:23:24 | 00:01:00 | 00:08:06 | |
| 13 | | 156:25:20 | 05:52:13 | 05:46:29 | |
| 14 | | 156:59:21 | 05:35:26 | 06:05:20 | |
| 15 | | 159:20:25 | 05:31:01 | 06:27:06 | |
| 16 | | 145:22:08 | 05:47:29 | 06:32:47 | |
| 17 | | 04:43:34 | 00:10:26 | 00:10:43 | |
| 18 | | 04:37:09 | 00:10:58 | 00:12:57 | |
| 19 | | 03:56:54 | 00:09:56 | 00:13:50 | |
| 20 | | 04:40:14 | 00:11:32 | 00:12:37 | |
| 21 | | 02:19:58 | 00:07:09 | 00:08:17 | |
| 22 | | 02:27:15 | 00:07:15 | 00:13:04 | |
| 23 | | 02:00:52 | 00:07:04 | 00:14:43 | |
| 24 | | 02:28:35 | 00:07:46 | 00:06:28 | |

**Table 14: Average execution times**

| configuration (weighting factors) | | fitness $\mu \pm \sigma$ | A $\mu \pm \sigma$ | B $\mu \pm \sigma$ | C $\mu \pm \sigma$ | D $\mu \pm \sigma$ | E $\mu \pm \sigma$ | G $\mu \pm \sigma$ | $(1-B)^2+(1-C)^2+(1-D)^2$ $\mu \pm \sigma$ |
|---|---|---|---|---|---|---|---|---|---|
| **ES.1** | (I) | 4.3570 ± *0.0062* | -0.6783 ± *0.0291* | 0.9535 ± *0.0016* | 0.1388 ± *0.0004* | 0.8795 ± *0.0078* | -161.8243 ± *4.3035* | 0.9997 ± *0.0001* | **0.7585** ± *0.0018* |
| **ES.2** | (II) | 5.9781 ± *0.0201* | 0.3052 ± *0.0175* | 0.8084 ± *0.0041* | 0.1307 ± *0.0005* | 0.9482 ± *0.0052* | -140.7128 ± *12.7537* | 0.9998 ± *0.0001* | **0.7951** ± *0.0008* |
| ES.3 | (III) | 7.5644 ± *0.0240* | 0.3938 ± *0.0087* | 0.7899 ± *0.0037* | 0.1244 ± *0.0015* | 0.9616 ± *0.0045* | -150.4708 ± *13.9084* | 0.9996 ± *0.0003* | 0.8123 ± *0.0036* |
| ES.4 | (I) | 4.1904 ± *0.0066* | -1.1596 ± *0.0353* | 0.9677 ± *0.0016* | 0.1335 ± *0.0010* | 0.7764 ± *0.0084* | -211.6199 ± *5.8625* | 0.9746 ± *0.0029* | 0.8020 ± *0.0043* |
| ES.5 | (II) | 5.7025 ± *0.0150* | 0.2546 ± *0.0202* | 0.8113 ± *0.0086* | 0.1296 ± *0.0014* | 0.8981 ± *0.0122* | -179.2861 ± *15.2293* | 0.9186 ± *0.0048* | 0.8038 ± *0.0039* |
| ES.6 | (III) | 7.2651 ± *0.0259* | 0.3779 ± *0.0148* | 0.7834 ± *0.0086* | 0.1266 ± *0.0010* | 0.9216 ± *0.0075* | -187.2385 ± *12.1825* | 0.9063 ± *0.0054* | 0.8160 ± *0.0054* |
| ES.7 | (I) | 2.3796 ± *0.0162* | -0.6813 ± *0.0769* | 0.9224 ± *0.0054* | 0.1317 ± *0.0014* | 0.3020 ± *0.0319* | -367.8852 ± *38.0888* | 0.2426 ± *0.0102* | 1.2483 ± *0.0472* |
| ES.8 | (II) | 3.8672 ± *0.0427* | 0.2165 ± *0.0310* | 0.7824 ± *0.0128* | 0.1408 ± *0.0022* | 0.5155 ± *0.0203* | -388.2234 ± *11.6880* | 0.2243 ± *0.0053* | 1.0209 ± *0.0201* |
| ES.9 | (III) | 5.2800 ± *0.0373* | 0.3384 ± *0.0154* | 0.7528 ± *0.0076* | 0.1347 ± *0.0016* | 0.5174 ± *0.0123* | -395.2126 ± *33.0168* | 0.2186 ± *0.0041* | 1.0430 ± *0.0123* |

**Table 9: Results for ES**

| configuration (weighting factors) | | fitness $\mu \pm \sigma$ | A $\mu \pm \sigma$ | B $\mu \pm \sigma$ | C $\mu \pm \sigma$ | D $\mu \pm \sigma$ | E $\mu \pm \sigma$ | G $\mu \pm \sigma$ | $(1-B)^2+(1-C)^2+(1-D)^2$ $\mu \pm \sigma$ |
|---|---|---|---|---|---|---|---|---|---|
| OSGA.1 | (I) | 2.9746 ± *0.1219* | -7.4695 ± *1.2465* | 0.8772 ± *0.0101* | 0.1297 ± *0.0016* | 0.2657 ± *0.0015* | -334.2880 ± *23.9643* | 0.9163 ± *0.0426* | 1.3118 ± *0.0029* |
| OSGA.2 | (I) | 2.9246 ± *0.0274* | -7.7324 ± *0.2614* | 0.8599 ± *0.0075* | 0.1289 ± *0.0022* | 0.2691 ± *0.0071* | -332.5402 ± *15.6849* | 0.9216 ± *0.0151* | 1.3128 ± *0.0110* |
| OSGA.3 | (I) | 2.9378 ± *0.1253* | -7.5260 ± *0.4706* | 0.8865 ± *0.0055* | 0.1265 ± *0.0005* | 0.2666 ± *0.0063* | -342.4165 ± *17.4174* | 0.9002 ± *0.0457* | 1.3138 ± *0.0085* |
| OSGA.4 | (I) | 2.9761 ± *0.0592* | -7.4787 ± *0.2615* | 0.8815 ± *0.0082* | 0.1274 ± *0.0011* | 0.2740 ± *0.0066* | -340.9637 ± *17.5956* | 0.9188 ± *0.0226* | 1.3027 ± *0.0095* |
| OSGA.5 | (II) | 3.0377 ± *0.0412* | 0.0750 ± *0.0871* | 0.6990 ± *0.0303* | 0.1281 ± *0.0010* | 0.2630 ± *0.0042* | -472.1380 ± *16.0459* | 0.1548 ± *0.0096* | 1.3949 ± *0.0146* |
| OSGA.6 | (II) | 3.1214 ± *0.0629* | 0.0705 ± *0.2048* | 0.7151 ± *0.0598* | 0.1269 ± *0.0012* | 0.2629 ± *0.0045* | -439.2752 ± *47.6515* | 0.1625 ± *0.0304* | 1.3903 ± *0.0380* |
| OSGA.7 | (II) | 3.1162 ± *0.0711* | 0.1437 ± *0.1504* | 0.6884 ± *0.0501* | 0.1280 ± *0.0008* | 0.2627 ± *0.0029* | -432.4444 ± *66.3843* | 0.1560 ± *0.0222* | 1.4035 ± *0.0298* |
| OSGA.8 | (II) | 3.0893 ± *0.0400* | 0.1507 ± *0.1277* | 0.6908 ± *0.0263* | 0.1268 ± *0.0016* | 0.2675 ± *0.0084* | -455.2424 ± *16.6219* | 0.1501 ± *0.0228* | 1.3955 ± *0.0273* |
| OSGA.9 | (III) | 4.3353 ± *0.0884* | 0.3533 ± *0.0775* | 0.6414 ± *0.0199* | 0.1266 ± *0.0009* | 0.2612 ± *0.0025* | -463.6659 ± *39.2622* | 0.1240 ± *0.0175* | 1.4376 ± *0.0177* |
| OSGA.10 | (III) | 4.3144 ± *0.0963* | 0.2751 ± *0.1130* | 0.6757 ± *0.0489* | 0.1265 ± *0.0012* | 0.2606 ± *0.0025* | -504.8659 ± *83.2736* | 0.1271 ± *0.0217* | 1.4173 ± *0.0358* |
| OSGA.11 | (III) | 4.3317 ± *0.0433* | 0.3628 ± *0.1227* | 0.6387 ± *0.0555* | 0.1276 ± *0.0008* | 0.2645 ± *0.0071* | -477.4945 ± *57.6697* | 0.1237 ± *0.0098* | 1.4357 ± *0.0367* |
| OSGA.12 | (III) | 4.2912 ± *0.0874* | 0.3046 ± *0.1240* | 0.6452 ± *0.0531* | 0.1266 ± *0.0011* | 0.2620 ± *0.0052* | -434.9428 ± *15.2230* | 0.1268 ± *0.0171* | 1.4363 ± *0.0458* |
| OSGA.13 | (I) | 3.1254 ± *0.0376* | -7.0884 ± *0.3938* | 0.9630 ± *0.0053* | 0.1270 ± *0.0009* | 0.2626 ± *0.0014* | -343.0525 ± *9.1134* | 0.8958 ± *0.0296* | 1.3073 ± *0.0038* |
| OSGA.14 | (I) | 3.1019 ± *0.0374* | -7.3593 ± *0.4811* | 0.9619 ± *0.0033* | 0.1269 ± *0.0005* | 0.2618 ± *0.0009* | -347.5358 ± *12.2619* | 0.9012 ± *0.0239* | 1.3087 ± *0.0021* |
| OSGA.15 | (I) | 3.1192 ± *0.0241* | -7.6938 ± *0.6074* | 0.9627 ± *0.0016* | 0.1271 ± *0.0012* | 0.2640 ± *0.0014* | -353.0963 ± *8.0522* | 0.9279 ± *0.0212* | 1.3050 ± *0.0024* |
| OSGA.16 | (I) | 3.0965 ± *0.0195* | -7.0703 ± *0.4560* | 0.9634 ± *0.0033* | 0.1269 ± *0.0005* | 0.2674 ± *0.0020* | -354.9677 ± *9.1950* | 0.8854 ± *0.0241* | 1.3004 ± *0.0024* |
| OSGA.17 | (II) | 3.3620 ± *0.0197* | 0.0133 ± *0.0897* | 0.7496 ± *0.0311* | 0.1297 ± *0.0010* | 0.2635 ± *0.0022* | -357.8750 ± *16.9727* | 0.2090 ± *0.0205* | 1.3636 ± *0.0144* |
| OSGA.18 | (II) | 3.5753 ± *0.3439* | 0.2280 ± *0.3971* | 0.5992 ± *0.3004* | 0.1827 ± *0.1056* | 0.4109 ± *0.2946* | -273.0839 ± *138.3514* | 0.1691 ± *0.0855* | 1.3638 ± *0.0080* |
| OSGA.19 | (II) | 3.3773 ± *0.0302* | 0.0599 ± *0.0960* | 0.7309 ± *0.0221* | 0.1295 ± *0.0015* | 0.2648 ± *0.0027* | -331.0050 ± *19.5051* | 0.2084 ± *0.0166* | 1.3712 ± *0.0090* |
| OSGA.20 | (II) | 3.3614 ± *0.0297* | 0.0486 ± *0.0486* | 0.7379 ± *0.0177* | 0.1285 ± *0.0017* | 0.2702 ± *0.0055* | -353.3163 ± *29.3771* | 0.2091 ± *0.0152* | 1.3612 ± *0.0127* |
| OSGA.21 | (III) | 4.5768 ± *0.0414* | 0.2831 ± *0.0691* | 0.7003 ± *0.0204* | 0.1274 ± *0.0010* | 0.2618 ± *0.0036* | -414.3977 ± *33.8977* | 0.1414 ± *0.0145* | 1.3966 ± *0.0149* |
| OSGA.22 | (III) | 4.5637 ± *0.0470* | 0.2857 ± *0.0693* | 0.6996 ± *0.0281* | 0.1291 ± *0.0009* | 0.2625 ± *0.0031* | -454.2134 ± *25.5217* | 0.1506 ± *0.0074* | 1.3935 ± *0.0140* |
| OSGA.23 | (III) | 4.5898 ± *0.0361* | 0.2995 ± *0.0923* | 0.6909 ± *0.0324* | 0.1290 ± *0.0021* | 0.2641 ± *0.0041* | -416.9518 ± *15.4548* | 0.1526 ± *0.0148* | 1.3968 ± *0.0185* |
| OSGA.24 | (III) | 4.5388 ± *0.0326* | 0.2674 ± *0.0825* | 0.6989 ± *0.0280* | 0.1273 ± *0.0009* | 0.2677 ± *0.0052* | -436.2067 ± *33.4633* | 0.1512 ± *0.0110* | 1.3893 ± *0.0188* |

**Table 10: Results for OSGA with a maximum selection pressure of 100**

| configuration (weighting factors) | | fitness $\mu \pm \sigma$ | A $\mu \pm \sigma$ | B $\mu \pm \sigma$ | C $\mu \pm \sigma$ | D $\mu \pm \sigma$ | E $\mu \pm \sigma$ | G $\mu \pm \sigma$ | $(1-B)^2+(1-C)^2+(1-D)^2$ $\mu \pm \sigma$ |
|---|---|---|---|---|---|---|---|---|---|
| OSGA.1 | (I) | 3.0390 ± *0.1263* | -7.4840 ± *0.7301* | 0.8688 ± *0.0139* | 0.1281 ± *0.0019* | 0.2693 ± *0.0045* | -320.3625 ± *10.6459* | 0.9526 ± *0.0110* | 1.3116 ± *0.0108* |
| OSGA.2 | (I) | 2.9569 ± *0.1069* | -7.5020 ± *0.2541* | 0.8593 ± *0.0096* | 0.1264 ± *0.0018* | 0.2635 ± *0.0032* | -327.8744 ± *18.5919* | 0.9290 ± *0.0227* | 1.3255 ± *0.0091* |
| OSGA.3 | (I) | 3.0663 ± *0.0373* | -7.0850 ± *0.6012* | 0.8627 ± *0.0114* | 0.1294 ± *0.0021* | 0.2681 ± *0.0062* | -309.6847 ± *12.6427* | 0.9453 ± *0.0194* | 1.3128 ± *0.0109* |
| OSGA.4 | (I) | 2.9861 ± *0.0688* | -7.7227 ± *0.5555* | 0.8826 ± *0.0178* | 0.1277 ± *0.0013* | 0.2708 ± *0.0097* | -332.0081 ± *10.9920* | 0.9304 ± *0.0249* | 1.3068 ± *0.0123* |
| OSGA.5 | (II) | 3.1272 ± *0.0298* | 0.1872 ± *0.1665* | 0.6721 ± *0.0412* | 0.1274 ± *0.0021* | 0.2621 ± *0.0016* | -412.0663 ± *48.7797* | 0.1566 ± *0.0310* | 1.4152 ± *0.0207* |
| OSGA.6 | (II) | 3.1260 ± *0.0646* | 0.2059 ± *0.1190* | 0.6664 ± *0.0341* | 0.1294 ± *0.0027* | 0.2611 ± *0.0037* | -407.7279 ± *55.5925* | 0.1462 ± *0.0252* | 1.4164 ± *0.0176* |
| OSGA.7 | (II) | 3.1430 ± *0.0613* | 0.1283 ± *0.0510* | 0.6858 ± *0.0063* | 0.1284 ± *0.0015* | 0.2639 ± *0.0067* | -392.3991 ± *53.5551* | 0.1596 ± *0.0181* | 1.4004 ± *0.0093* |
| OSGA.8 | (II) | 3.2258 ± *0.1015* | 0.3209 ± *0.3471* | 0.5613 ± *0.2817* | 0.1559 ± *0.0554* | 0.4219 ± *0.2892* | -343.1475 ± *174.3164* | 0.1310 ± *0.0668* | 1.4052 ± *0.0703* |
| OSGA.9 | (III) | 4.4018 ± *0.0655* | 0.4193 ± *0.0391* | 0.6292 ± *0.0136* | 0.1282 ± *0.0013* | 0.2654 ± *0.0019* | -457.6038 ± *37.6468* | 0.1148 ± *0.0024* | 1.4374 ± *0.0083* |
| OSGA.10 | (III) | 4.4057 ± *0.0502* | 0.3408 ± *0.0591* | 0.6590 ± *0.0248* | 0.1283 ± *0.0019* | 0.2648 ± *0.0083* | -455.6775 ± *33.7490* | 0.1194 ± *0.0130* | 1.4173 ± *0.0210* |
| OSGA.11 | (III) | 4.4198 ± *0.0344* | 0.3619 ± *0.0512* | 0.6475 ± *0.0169* | 0.1280 ± *0.0014* | 0.2628 ± *0.0045* | -432.8915 ± *31.1507* | 0.1241 ± *0.0088* | 1.4285 ± *0.0190* |
| OSGA.12 | (III) | 4.4324 ± *0.0440* | 0.2555 ± *0.0766* | 0.6870 ± *0.0294* | 0.1285 ± *0.0022* | 0.2639 ± *0.0060* | -434.6844 ± *29.1328* | 0.1375 ± *0.0110* | 1.4002 ± *0.0181* |
| OSGA.13 | (I) | 3.1194 ± *0.0155* | -7.3911 ± *0.5308* | 0.9641 ± *0.0071* | 0.1273 ± *0.0006* | 0.2617 ± *0.0009* | -354.6142 ± *6.6739* | 0.9122 ± *0.0204* | 1.3080 ± *0.0013* |
| OSGA.14 | (I) | 3.1260 ± *0.0348* | -7.1229 ± *0.4378* | 0.9609 ± *0.0037* | 0.1278 ± *0.0008* | 0.2634 ± *0.0023* | -346.3559 ± *0.3813* | 0.9002 ± *0.0101* | 1.3049 ± *0.0044* |
| OSGA.15 | (I) | 3.1314 ± *0.0236* | -7.0845 ± *1.0084* | 0.9631 ± *0.0052* | 0.1276 ± *0.0012* | 0.2661 ± *0.0021* | -346.0999 ± *11.9384* | 0.8985 ± *0.0490* | 1.3010 ± *0.0039* |
| OSGA.16 | (I) | 3.1338 ± *0.0266* | -7.0331 ± *0.3920* | 0.9632 ± *0.0040* | 0.1268 ± *0.0009* | 0.2671 ± *0.0011* | -343.6581 ± *18.9551* | 0.8969 ± *0.0224* | 1.3010 ± *0.0026* |
| OSGA.17 | (II) | 3.3600 ± *0.0263* | 0.0151 ± *0.1024* | 0.7412 ± *0.0250* | 0.1302 ± *0.0010* | 0.2655 ± *0.0030* | -350.8687 ± *17.8131* | 0.2141 ± *0.0158* | 1.3637 ± *0.0105* |
| OSGA.18 | (II) | 3.3298 ± *0.0234* | 0.1501 ± *0.0797* | 0.7221 ± *0.0166* | 0.1284 ± *0.0019* | 0.2640 ± *0.0037* | -365.6197 ± *16.7608* | 0.1742 ± *0.0143* | 1.3790 ± *0.0080* |
| OSGA.19 | (II) | 3.3567 ± *0.0366* | 0.0943 ± *0.0829* | 0.7367 ± *0.0309* | 0.1288 ± *0.0014* | 0.2627 ± *0.0034* | -349.0628 ± *19.7474* | 0.1842 ± *0.0109* | 1.3729 ± *0.0176* |
| OSGA.20 | (II) | 3.3795 ± *0.0209* | 0.0168 ± *0.1402* | 0.7474 ± *0.0275* | 0.1286 ± *0.0013* | 0.2689 ± *0.0048* | -348.0070 ± *22.4220* | 0.2170 ± *0.0257* | 1.3585 ± *0.0204* |
| OSGA.21 | (III) | 4.5685 ± *0.0345* | 0.3407 ± *0.0772* | 0.6662 ± *0.0286* | 0.1283 ± *0.0012* | 0.2647 ± *0.0038* | -387.5015 ± *58.6999* | 0.1491 ± *0.0154* | 1.4128 ± *0.0208* |
| OSGA.22 | (III) | 4.5663 ± *0.0376* | 0.2866 ± *0.0482* | 0.6960 ± *0.0206* | 0.1283 ± *0.0009* | 0.2607 ± *0.0022* | -427.0658 ± *33.0077* | 0.1484 ± *0.0113* | 1.3993 ± *0.0157* |
| OSGA.23 | (III) | 4.6165 ± *0.0275* | 0.2651 ± *0.1155* | 0.6985 ± *0.0369* | 0.1286 ± *0.0020* | 0.2685 ± *0.0071* | -383.0627 ± *42.5452* | 0.1640 ± *0.0232* | 1.3867 ± *0.0213* |
| OSGA.24 | (III) | 4.6079 ± *0.0353* | 0.2134 ± *0.0787* | 0.7224 ± *0.0258* | 0.1275 ± *0.0006* | 0.2659 ± *0.0034* | -396.3235 ± *22.0777* | 0.1614 ± *0.0093* | 1.3780 ± *0.0125* |

**Table 11: Results for OSGA with a maximum selection pressure of 1000**

| configuration (weighting factors) | | fitness $\mu \pm \sigma$ | A $\mu \pm \sigma$ | B $\mu \pm \sigma$ | C $\mu \pm \sigma$ | D $\mu \pm \sigma$ | E $\mu \pm \sigma$ | G $\mu \pm \sigma$ | $(1-B)^2 + (1-C)^2 + (1-D)^2$ $\mu \pm \sigma$ |
|---|---|---|---|---|---|---|---|---|---|
| GA.1 | (I) | 2.8447 ± *0.0300* | -8.6780 ± *0.5577* | 0.8848 ± *0.0189* | 0.1278 ± *0.0008* | 0.2662 ± *0.0069* | -347.9151 ± *13.4363* | 0.9138 ± *0.0180* | 1.3129 ± *0.0055* |
| GA.2 | (I) | 2.8551 ± *0.0411* | -7.7880 ± *0.7012* | 0.8895 ± *0.0117* | 0.1268 ± *0.0011* | 0.2666 ± *0.0038* | -364.3555 -± *17.9481* | 0.8794 ± *0.0404* | 1.3127 ± *0.0070* |
| GA.3 | (I) | 2.8895 ± *0.0710* | -7.7873 ± *0.3333* | 0.8815 ± *0.0094* | 0.1276 ± *0.0016* | 0.2690 ± *0.0071* | -361.2115 ± *24.5732* | 0.9015 ± *0.0353* | 1.3096 ± *0.0121* |
| GA.4 | (I) | 2.8930 ± *0.0971* | -8.1451 ± *0.6438* | 0.9046 ± *0.0089* | 0.1264 ± *0.0005* | 0.2829 ± *0.0064* | -371.0544 ± *15.9012* | 0.9026 ± *0.0092* | 1.2866 ± *0.0105* |
| GA.5 | (II) | 3.1644 ± *0.1906* | 0.3813 ± *0.3131* | 0.5418 ± *0.2710* | 0.1593 ± *0.0648* | 0.4084 ± *0.2958* | -367.6429 ± *187.5801* | 0.1030 ± *0.0516* | 1.4318 ± *0.0380* |
| GA.6 | (II) | 3.0715 ± *0.0711* | 0.3100 ± *0.1308* | 0.6375 ± *0.0589* | 0.1283 ± *0.0025* | 0.2625 ± *0.0050* | -439.7807 ± *33.3116* | 0.1297 ± *0.0108* | 1.4387 ± *0.0446* |
| GA.7 | (II) | 3.0603 ± *0.0654* | 0.2314 ± *0.1459* | 0.6430 ± *0.0435* | 0.1266 ± *0.0004* | 0.2694 ± *0.0084* | -406.7175 ± *16.4806* | 0.1429 ± *0.0309* | 1.4260 ± *0.0382* |
| GA.8 | (II) | 3.1168 ± *0.0539* | 0.2024 ± *0.1280* | 0.6717 ± *0.0272* | 0.1263 ± *0.0018* | 0.2720 ± *0.0084* | -421.8528 ± *57.4359* | 0.1504 ± *0.0215* | 1.4019 ± *0.0281* |
| GA.9 | (III) | 4.2663 ± *0.0588* | 0.4406 ± *0.0906* | 0.6101 ± *0.0302* | 0.1287 ± *0.0011* | 0.2608 ± *0.0028* | -516.0732 ± *75.3598* | 0.1029 ± *0.0146* | 1.4587 ± *0.0215* |
| GA.10 | (III) | 4.3189 ± *0.1411* | 0.4366 ± *0.0459* | 0.6127 ± *0.0206* | 0.1268 ± *0.0011* | 0.2673 ± *0.0046* | -475.9109 ± *69.0845* | 0.1086 ± *0.0182* | 1.4498 ± *0.0131* |
| GA.11 | (III) | 4.2513 ± *0.0360* | 0.3782 ± *0.0968* | 0.6230 ± *0.0442* | 0.1273 ± *0.0010* | 0.2652 ± *0.0092* | -483.3367 ± *49.8040* | 0.1107 ± *0.0213* | 1.4457 ± *0.0283* |
| GA.12 | (III) | 4.3498 ± *0.1001* | 0.4582 ± *0.0597* | 0.6068 ± *0.0313* | 0.1256 ± *0.0013* | 0.2785 ± *0.0145* | -461.8841 ± *65.3825* | 0.1097 ± *0.0125* | 1.4409 ± *0.0252* |
| GA.13 | (I) | 2.7326 ± *0.0362* | -8.9548 ± *0.2734* | 0.9737 ± *0.0015* | 0.1269 ± *0.0005* | 0.2623 ± *0.0012* | -493.0023 ± *28.3782* | 0.8571 ± *0.0143* | 1.3072 ± *0.0016* |
| GA.14 | (I) | 2.7119 ± *0.0292* | -8.2744 ± *0.6513* | 0.9720 ± *0.0033* | 0.1266 ± *0.0008* | 0.2620 ± *0.0014* | -488.1769 ± *17.3524* | 0.8126 ± *0.0429* | 1.3083 ± *0.0034* |
| GA.15 | (I) | 2.6555 ± *0.0583* | -7.7567 ± *1.1280* | 0.9695 ± *0.0043* | 0.1263 ± *0.0004* | 0.2643 ± *0.0014* | -529.2015 ± *14.1687* | 0.7817 ± *0.0746* | 1.3056 ± *0.0015* |
| GA.16 | (I) | 2.6749 ± *0.0566* | -7.8767 ± *1.2966* | 0.9710 ± *0.0043* | 0.1265 ± *0.0007* | 0.2686 ± *0.0054* | -508.0574 ± *36.2673* | 0.7843 ± *0.0620* | 1.2988 ± *0.0080* |
| GA.17 | (II) | 3.1999 ± *0.0684* | 0.0428 ± *0.1504* | 0.7267 ± *0.0321* | 0.1292 ± *0.0015* | 0.2659 ± *0.0042* | -425.9723 ± *39.5065* | 0.1828 ± *0.0147* | 1.3729 ± *0.0240* |
| GA.18 | (II) | 3.1968 ± *0.0299* | 0.1088 ± *0.1395* | 0.7054 ± *0.0328* | 0.1300 ± *0.0041* | 0.2686 ± *0.0089* | -404.2369 ± *10.5182* | 0.1661 ± *0.0273* | 1.3799 ± *0.0254* |
| GA.19 | (II) | 3.2193 ± *0.0545* | 0.1176 ± *0.1764* | 0.7055 ± *0.0460* | 0.1278 ± *0.0011* | 0.2772 ± *0.0149* | -397.3209 ± *30.8640* | 0.1748 ± *0.0241* | 1.3723 ± *0.0227* |
| GA.20 | (II) | 3.3198 ± *0.2279* | 0.3217 ± *0.3478* | 0.5612 ± *0.2810* | 0.1671 ± *0.0784* | 0.4225 ± *0.2890* | -335.7993 ± *171.9184* | 0.1348 ± *0.0689* | 1.3885 ± *0.0397* |
| GA.21 | (III) | 4.3541 ± *0.0342* | 0.3185 ± *0.1437* | 0.6471 ± *0.0512* | 0.1265 ± *0.0019* | 0.2632 ± *0.0046* | -415.1718 ± *25.8177* | 0.1296 ± *0.0226* | 1.4331 ± *0.0399* |
| GA.22 | (III) | 4.3899 ± *0.0227* | 0.3081 ± *0.0821* | 0.6684 ± *0.0376* | 0.1276 ± *0.0008* | 0.2629 ± *0.0035* | -466.7078 ± *48.0598* | 0.1283 ± *0.0085* | 1.4158 ± *0.0273* |
| GA.23 | (III) | 4.3889 ± *0.0350* | 0.3442 ± *0.1139* | 0.6451 ± *0.0471* | 0.1285 ± *0.0013* | 0.2664 ± *0.0065* | -431.7201 ± *40.1796* | 0.1297 ± *0.0186* | 1.4258 ± *0.0396* |
| GA.24 | (III) | 4.4178 ± *0.0242* | 0.2456 ± *0.1157* | 0.6887 ± *0.0391* | 0.1272 ± *0.0010* | 0.2749 ± *0.0146* | -446.6220 ± *35.6724* | 0.1417 ± *0.0192* | 1.3862 ± *0.0441* |

**Table 12: Results for GA**

| configuration | MAX(B) ($\mu \pm \sigma$) | MAX(C) ($\mu \pm \sigma$) | MAX(D) ($\mu \pm \sigma$) | MIN($(1-B)^2 + (1-C)^2 + (1-D)^2$) | | | |
|---|---|---|---|---|---|---|---|
| | | | | B ($\mu \pm \sigma$) | C ($\mu \pm \sigma$) | D ($\mu \pm \sigma$) | $(1-B)^2 + (1-C)^2 + (1-D)^2$ ($\mu \pm \sigma$) |
| NSGA.1 | 0.8582 ± *0.0269* | 0.2345 ± *0.0472* | 1.0000 ± *0.0000* | 0.7395 ± *0.1800* | 0.1676 ± *0.0327* | 0.5795 ± *0.1387* | 0.9797 ± *0.1376* |
| NSGA.2 | 0.9157 ± *0.0250* | 0.3371 ± *0.1075* | 1.0000 ± *0.0000* | 0.8895 ± *0.0374* | 0.2215 ± *0.0543* | 0.6907 ± *0.0762* | 0.7221 ± *0.0957* |
| NSGA.3 | 0.9340 ± *0.0103* | 0.3071 ± *0.0558* | 1.0000 ± *0.0000* | 0.8642 ± *0.0939* | 0.1835 ± *0.0433* | 0.5839 ± *0.1811* | 0.8931 ± *0.1860* |
| NSGA.4 | 0.9598 ± *0.0082* | 0.3385 ± *0.0444* | 1.0000 ± *0.0000* | 0.7715 ± *0.2479* | 0.1766 ± *0.0516* | 0.5018 ± *0.2037* | 1.0628 ± *0.1188* |
| **NSGA.5** | 0.9755 ± *0.0045* | 0.3970 ± *0.0552* | 1.0000 ± *0.0000* | 0.8496 ± *0.0503* | 0.4025 ± *0.0695* | 0.6723 ± *0.0681* | **0.6466** ± *0.1174* |
| NSGA.6 | 0.9727 ± *0.0074* | 0.3935 ± *0.0436* | 1.0000 ± *0.0000* | 0.8293 ± *0.0804* | 0.2415 ± *0.0277* | 0.7033 ± *0.0334* | 0.6992 ± *0.0412* |
| NSGA.7 | 0.9716 ± *0.0037* | 0.3354 ± *0.0714* | 1.0000 ± *0.0000* | 0.8196 ± *0.0644* | 0.2267 ± *0.0543* | 0.8223 ± *0.0624* | 0.6709 ± *0.0983* |
| **NSGA.8** | 0.9768 ± *0.0042* | 0.3787 ± *0.0974* | 1.0000 ± *0.0000* | 0.8080 ± *0.0407* | 0.2538 ± *0.0860* | 0.8241 ± *0.0431* | **0.6334** ± *0.1266* |

**Table 13: Results for NSGA-II**

runs for each test setup. In Table 13 we present maximum values achieved for B, C, and D found in solutions present in the Pareto front; furthermore we also report on the best solutions that are optimal (minimal) with respect to the fitness function $(1 - B)^2 + (1 - C)^2 + (1 - D)^2$, which was not used by the algorithms. This value is also given for all results produced by the other tested algorithms.

As we can see in Table 14, runs using the weighting factor configuration I are much more time expensive than those using configurations II and III. The reason for this is the number of documents clustered: All test runs performed with configuration I yield a much higher average value for parameter B, which measures the number of documents incorporated in the clusters. In fact this is a bit surprising as this configuration has the lowest weighting factor value for $\beta$ (see Table 4), which defines the weighting of parameter $B$. This indicates that not the weighting factors on their own but rather their combination lead to the results we see here; weighting factor tuning is in this context a challenging task on its own.

Furthermore, we can also retain that evolution strategy performs best of all single-objective algorithms tested here. Not only the average execution times justify this statement (Table 14) but also the comparison of the parameter values measured: Comparing the last columns of the results shown in Tables 9 - 12, which outline the combination of the most interesting parameters (B, C, and D), we can see that already the worst result of ES (1.2483) outperforms all test results achieved using GAs and OSGAs. Concerning algorithm parameters of ES, the 1+1 strategy generates the best solutions. Considering GA and OSGA, there is no obvious preference for either algorithm for this application scenario; regarding offspring selection settings we see that increasing the maximum selection pressure to values higher than 100 does not seem to have a significant positive effect. When comparing ES to the multi-objective approach, we can see that the NSGA-II produces results with qualities similar to evolution strategy results; still we have to admit that the execution times for the NSGA-II runs are significantly higher (Table 14). As we see in Table 13, the best results obtained are produced by the NSGA-II with population size 100 and 10% or 100% mutation rate; these results outperform all results achieved with ES.

# 4. CONCLUSION AND OUTLOOK

In this paper we have presented an analysis on keyword cluster optimization using evolutionary algorithms; both single-objective and multi-objective approaches were tested with several configurations. We see that evolution strategy performs best of all single-objective methods as it creates best solutions in rather short time. The NSGA-II provides results with comparable quality; however, the average execution times exceed the runtime of ES.

When it comes to using this approach in query extension we suggest using the NSGA-II as it covers various parts of the solution space and thus generates solutions appropriate for different user requirements: Users who want to choose only the most significant words for query extension would use a solution with a high $C$ and $D$ value, whereas users desiring a more broaden search would need a solution with a high $B$ value. To achieve the same possibilities with ES it would be necessary to generate one solution per user requirement (manifesting in different weighting factor settings) and spend a lot more time on weighting factor tuning. As shown in Section 3.3, this kind of optimization is a challenging task and is not necessary when using the NSGA-II.

To use the generated keyword clusters in practice we are currently working on a new search for PubMed data using query extension to find more significant results. For the application of the here discussed biomedical information retrieval approach we will invest even more effort in the identification of optimal clusters using bigger population sizes and higher limits for the number of evaluated solutions (even though this will require more runtime).

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