4.4. *Comparison Results and Analysis*

Tenfold cross validation sampling is adopted across all the feature selection algorithms. The performance evaluation is carried out by measuring accuracy and reduction rate by using KNN (1-NN) as the classification algorithm. The predictive accuracy and reduction rate reported are the average obtained over tenfold sampling. *Table 3* depicts the comparison between classification accuracies of 1-NN and the proposed MO-Micro-CHC algorithm. The results show that the suggested algorithm achieves higher accuracy in most of the domains as compared to 1-NN. Concerning reduction rate, there is more than 80% reduction of features except in case of *iris* dataset.

Table 3. Comparison Results of MO-Micro-CHC with I-NN Classification Accuracy

Datasets	1-NN Accuracy	MO-Micro-CHC Accuracy	MO-Micro-CHC Reduction Rate (RR)
Spambase	81.89	**99.30**	87.19
Waveform	89.90	**99.11**	87.50
Dermatology	89.79	**99.44**	94.12
Ionosphere	90.00	**99.42**	87.87
WDBC	97.76	**98.21**	83.33
German	61.00	**100**	95.00
Vehicle	65.17	**80.90**	88.89
Zoo	**100**	**100**	93.75
Australian	97.82	**100**	92.85
Wine	**100**	96.59	92.30
Breast Cancer	97.46	**99.70**	88.89
WBC	96.32	**98.43**	88.89
Glass	95.34	**99.28**	88.88
Heart	94.44	**99.55**	92.30
Iris	98.33	**100**	50.00

The proposed algorithm is further compared with five algorithms SFS, SBS, NSGA-II and MOEA/D in *Table 4*. We have taken results for SFS, SBS, NSGA-II approaches from [Paul and Das, (2015)] as shown in *Table 4*. The results demonstrate that MO-Micro-CHC attains higher classification accuracy in all the fourteen domains. The reduction rates achieved are also higher in all the domains. This confirms that MO-Micro-CHC converges to better non-dominated solutions with reference to accuracy and reduction rate.

Table 4. Comparison of MO-Micro-CHC with SFS, SBS, DEMOFS, NSGA-II and MOEA/D

Algorithm Datasets	SFS		SBS		NSGA-II		MOEA/D		MO-Micro-CHC	
	Acc	RR	Acc	RR	Acc	RR	Acc	RR	Acc	RR
Spambase	87.40	37.89	87.01	34.56	88.25	3.50	88.48	54.38	**99.30**	**87.19**
Waveform	77.82	54.00	78.46	54.25	80.14	1.50	83.65	60.00	**99.11**	**87.5**
Ionosphere	88.70	78.82	85.92	73.23	87.06	2.94	88.31	66.17	**99.42**	**87.87**
WDBC	90.12	53.66	89.77	40.66	96.34	0.00	94.06	55.00	**98.21**	**83.33**
German	68.20	49.16	65.80	55.00	71.02	4.16	71.30	56.25	**100**	**95.00**
Vehicle	68.56	40.00	67.34	40.55	68.06	3.88	65.26	49.44	**80.90**	**88.89**
Zoo	94.89	47.05	98.00	23.52	94.00	18.23	95.42	35.29	**100**	**93.75**
Australian	83.02	73.57	82.83	78.57	84.45	5.00	84.64	66.42	**100**	**92.85**
Wine	91.44	53.84	91.44	42.30	95.90	13.84	96.05	46.90	**96.59**	**92.30**
Breast Cancer	95.14	39.00	94.85	39.00	96.05	2.00	96.53	57.00	**99.70**	**88.89**
WBC	95.99	28.88	95.13	18.88	95.86	4.44	96.05	53.33	**98.43**	**88.89**
Glass	63.10	35.55	63.61	28.57	66.77	17.77	67.76	51.11	**99.28**	**88.88**
Heart	65.12	68.33	62.59	61.66	78.89	0.00	80.00	11.66	**99.55**	**92.30**
Iris	93.33	17.5	93.33	35.00	96.03	50.00	97.27	**50.00**	**100**	**50.00**

[Spolaor et al., (2010)] have done extensive work in the domain of feature selection. They have applied five distinct measures– Attribute Class Correlation (AC), Laplacian Score (LS), Inconsistent Example Pairs (IP), Inter-Class Distance (IE) and Representation Entropy (RE)- for feature selection. They have made ten combination of these five objective measures also optimized by using NSGA-II [Deb et al., (2002)] to obtain the best possible subset of features. Again, the results shown in *Table 5* for all of the above said approaches are taken from [Paul and Das, (2015)].The classification accuracy and reduction rates generated by MOGA-FS and MOEA/D are compared with the proposed approach, i.e., MO-Micro-CHC by applying rank-based method. The ranking is given from 1 to 12 for each dataset with rank 1 allotted to each of the method with maximum accuracy and increasing ranks for decreasing accuracies. Subsequent to that, an average rank is calculated for different datasets. Hence, smallest rank method may be considered as the best among the others. Whenever the results are same, then, the ranks are divided between them. The same ranking system is followed for Reduction Rates as well. *Table 5* presents the results of all MOGA-FS methods with different combinations of the criteria taken two at a time, MOEA/D and the proposed MO-Micro-CHC along with their ranks for three datasets (Dermatology, Vehicle and Wine) found common in these research works. The results show that MO-Micro-CHC has the top rank of 1 among the further methods of MOGA-FS and MOEA/D in case of classification accuracy. For reduction rates, MO-Micro-CHC and AC+LS are the two top ranking algorithms, however, AC+LS performs worse regarding accuracy. *Table 5* again establishes that the proposed algorithm settles for a better trade-off in between accuracy and reduction rate which is graphically depicted in Fig. 1, 2 &3.

Table 5. Comparison of MOGA-FS,MOEA/D and MO-Micro-CHC on the bases of classification accuracy and feature reduction rate (RR)

Feature selection procedure	**Dermatology**		**Vehicle**		**Wine**		**Average Rank of Acc (RR)**
	Acc	**RR**	**Acc**	**RR**	**Acc**	**RR**	
IE+AC	91.03(7)	23.14 (10)	72.43 (5)	6.85 (10)	93.24 (3)	37.69 (10)	5.00 (10)
IE+IP	93.28 (6)	00.00 (12)	74.00 (2)	00.00 (12)	92.12 (4.5)	00.00 (11.5)	4.16 (11.83)
IE+RE	94.11 (4)	01.76 (11)	73.96 (3)	00.19 (11)	92.12 (4.5)	00.00 (11.5)	3.83 (11.16)
IE+LS	90.67 (8)	33.53 (9)	72.74 (4)	14.07 (9)	89.35 (8)	64.62 (8)	6.66 (8.66)
AC+IP	62.75 (11)	85.39 (3)	69.99 (6)	62.59 (7)	89.93 (7)	78.46 (4)	8.00 (4.66)
AC+RE	93.46 (5)	40.59 (8)	63.84 (10)	88.89 (2.5)	90.02 (6)	69.74 (6)	7.00 (5.5)
AC+LS	65.38 (12)	**94.12** (1.5)	52.49 (11.5)	**94.44** (1.5)	83.10 (11)	88.46 (2)	11.5 (**1.66**)
IP+RE	96.08 (3)	52.35 (5)	67.62 (8)	76.30 (5)	77.48 (12)	69.23 (5)	7.66 (5)
IP+LS	80.73 (10)	71.67 (4)	68.44 (7)	63.33 (6)	89.31 (9)	83.85 (3)	8.66 (4.33)
RE+LS	88.99 (9)	43.73 (7)	52.49 (11.5)	**94.44** (1.5)	87.61 (10)	69.23 (7)	10.16 (5.16)
MOEA/D	96.13 (2)	45.76 (6)	65.26 (9)	49.44 (8)	96.05 (2)	46.90 (9)	4.33 (7.66)
MO-Micro-CHC	**99.44** (1)	**94.12** (1.5)	**80.90** (1)	88.89 (2.5)	**96.59** (1)	**92.30** (1)	**1**(**1.66**)

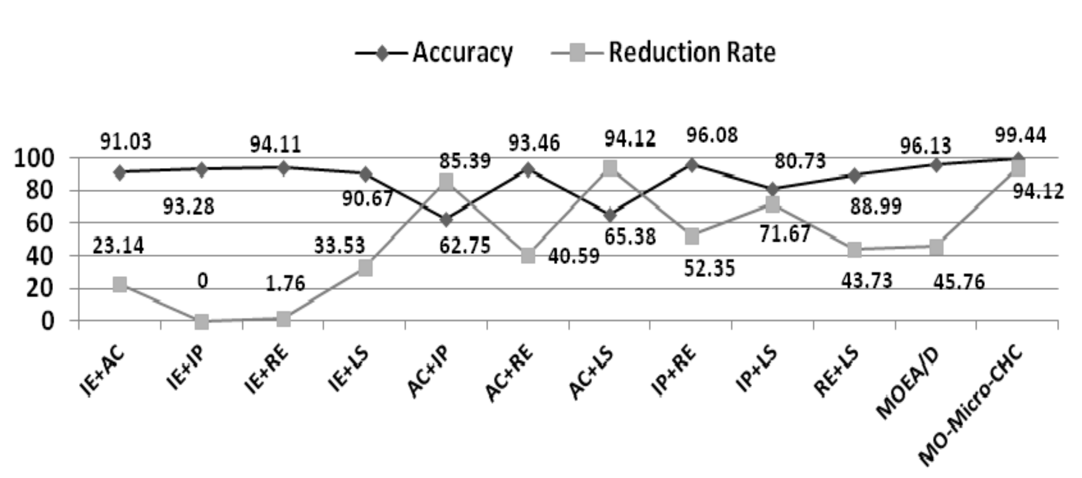

Fig.1.Tradeoff between Accuracy and Reduction Rates for Dermatology Dataset

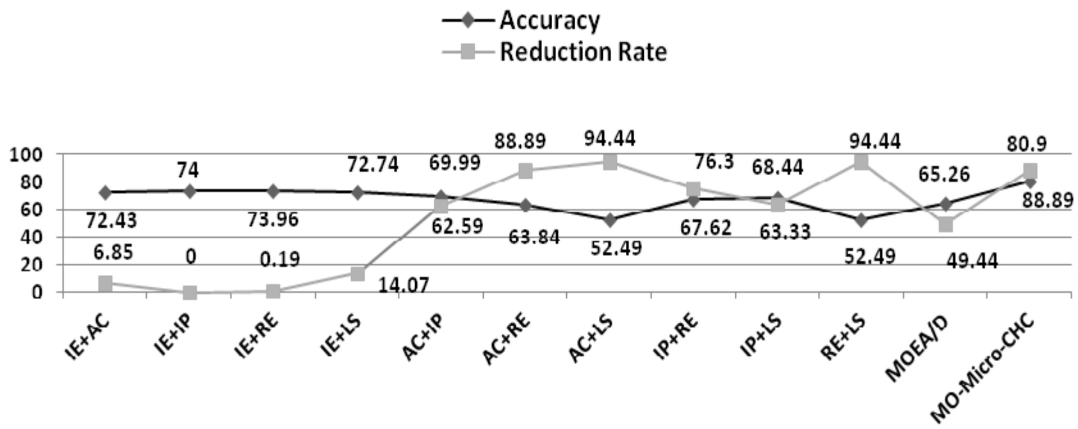

Fig.2. Tradeoff between Accuracy and Reduction Rates for Vehicle Dataset

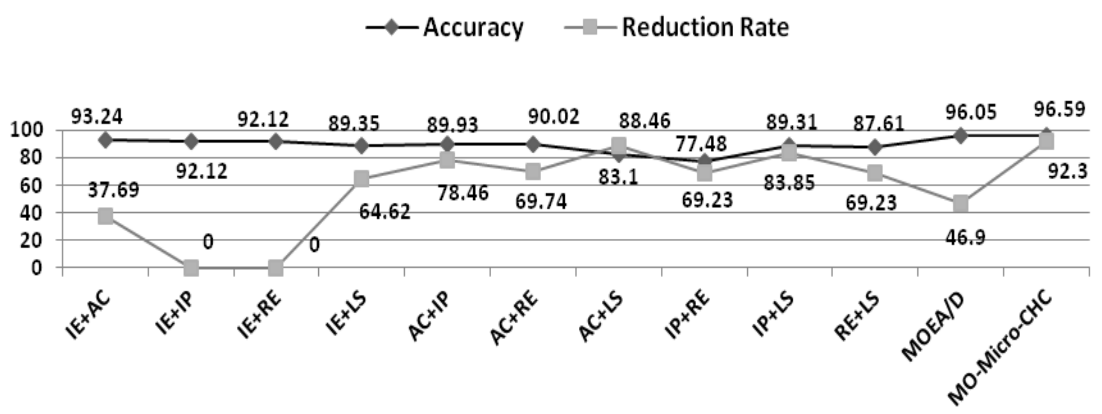

Fig.3. Tradeoff between Accuracy and Reduction Rates for Wine Dataset

The algorithm is further compared with MO-CHC for feature selection to study the behavior of the two algorithms concerning predictive accuracy, reduction rate and run-time. The comparison is shown in *Table 6*. We have used Wilcoxen signed rank test to see if there is any difference among the two algorithms regarding accuracy and reduction rate. The test results are negative with p values 0.255 and 0.635 for accuracy and reduction rates respectively. Hence, we can conclude that the two algorithms realize comparable accuracy and reduction rates. Furthermore, MO-Micro-CHC algorithm is far better in terms of execution time. It achieves a minimum and maximum speed gain of 2.17 and 11.0 respectively.

Table 6. Accuracy, Reduction Rate and Time comparison in between MOCHC and MO-Micro-CHC for Feature Selection

Datasets	**Accuracy of MO-CHC**	**RR of MO-CHC**	**Time (in sec) of MO-CHC**	**Accuracy of MO-Micro-CHC**	**RR of MO-Micro-CHC**	**Time (in sec) of MO-Micro-CHC (gain)**
Spambase	99.26	**98.43**	3387	**99.30**	87.19	1264 (2.67)
Waveform	98.78	**97.56**	3614	**99.11**	87.5	1306 (2.76)
Dermatology	99.32	**94.28**	305	**99.44**	94.12	140(2.17)
Ionosphere	97.56	**96.96**	242	**99.42**	87.87	34(7.11)
WDBC	**99.79**	**88.88**	251	98.21	83.33	52 (4.82)
German	**100**	**95.00**	368	**100**	95.00	72 (5.11)
Vehicle	78.52	**94.73**	228	**80.90**	88.89	70 (3.25)
Zoo	**100**	**93.75**	259	**100**	**93.75**	40 (6.47)
Australian	**100**	**92.85**	242	**100**	**92.85**	22 (11.0)
Wine	**100**	**92.30**	188	96.59	**92.30**	25 (8.54)
Breast Cancer	98.67	72.34	239	**99.70**	**88.89**	31 (7.70)
WBC	97.31	88.88	165	**98.43**	**88.89**	32 (5.15)
Glass	96.19	66.66	216	**99.28**	**88.88**	28 (7.71)
Heart	**100**	**92.30**	162	99.55	**92.30**	21 (7.71)
Iris	98.66	**50.00**	117	**100**	**50.00**	34 (3.44)

5. Conclusion

In this paper, we have devised a novel algorithm, Multi-objective Micro-CHC, for feature selection. The proposed Micro-CHC is compared with four similar algorithms based on accuracy and reduction. Since the Multi-objective micro-CHC attains high predictive performance and reduction rates in all the domains considered in this study, we can conclude that it finds more informative set of feature subsets. The suggested algorithm is also compared with several combinations of feature selection criteria for multi-objective function [Spolaor et al., (2010)] and MOEA/D [Paul and Das, (2015)]. The presentation of the proposed algorithm regarding accuracy is outstanding with top rank. MO-Micro-CHC stands at par with the top approach, (MOGA-FS with AC+LS) out of total twelve approaches tested. Looking at the accuracy and reduction rate trade-off, the performance of the suggested algorithm is quite satisfactory. For future work, we will use multi-objective parallel genetic search algorithms for multi-objective feature/instance selection.

References

[1] Ahuja, J.; Ratnoo, S. D. (2015): Feature Selection using Multi-objective Genetic Algorithm: A Hybrid Approach. ACM Recommender System 2012 Workshop on Recommendation Utility Evaluation: Beyond RMSE, Dublin, Ireland, 14(1), pp. 26–37.

[2] Anusha, M.; Sathiaseelan, J. G. R. (2015): Feature Selection Using K-Means Genetic Algorithm for Multi-objective Optimization. Procedia Computer Science, 3rd International Conference on Recent Trends in Computing (ICRTC), 57, pp. 1074–1080.

[3] Cano, J. R.; Herrera, F.; Lozano, M. (2003): Using evolutionary algorithms as instance selection for data reduction in KDD: an experimental study. IEEE Transactions on Evolutionary Computation, 7(6), pp. 561–575.

[4] Cano, J. R.; Herrera, F.; Lozano, M. (2005): Stratification for scaling up evolutionary prototype selection. Pattern Recognition Letters, 26(7), pp. 953–963.

[5] Coello, C. A. C. C.; Pulido, G. T. (2001): A Micro-Genetic Algorithm for Multiobjective Optimization. International Conference on Evolutionary Multi-Criterion Optimization, Lecture Notes in Computer Science, Springer, Berlin, Heidelberg, pp. 126–140.

[6] Deb, K.; Pratap, A.; Agarwal, S.; Meyarivan, T. (2002): A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II. Transaction Evolutionary Computation, 6(2), pp. 182–197.

[7] Derrac, J.; García, S.; Herrera, F. (2009): A First Study on the Use of Coevolutionary Algorithms for Instance and Feature Selection. Hybrid Artificial Intelligence Systems, Lecture Notes in Computer Science, E. Corchado, X. Wu, E. Oja, Á. Herrero, and B. Baruque, eds., Springer Berlin Heidelberg, pp. 557–564.

[8] Derrac, J.; García, S.; Herrera, F. (2010): A Survey on Evolutionary Instance Selection and Generation. International Journal of Applied Metaheuristic Computing, 1(1), pp. 60–92.

[9] Derrac, J.; Triguero, I.; Garcia, S.; Herrera, F. (2012): Integrating Instance Selection, Instance Weighting, and Feature Weighting for Nearest Neighbor Classifiers by Coevolutionary Algorithms. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, 42(5), pp. 1383–1397.

[10] Forman, G. (2003): An Extensive Empirical Study of Feature Selection Metrics for Text Classification. Journal of Machine Learning Research, 3, pp. 1289–1305.

[11] Garcia, S.; Derrac, J.; Cano, J.; Herrera, F. (2012): Prototype Selection for Nearest Neighbor Classification: Taxonomy and Empirical Study. IEEE Transactions on Pattern Analysis and Machine Intelligence, 34(3), pp. 417–435.

[12] García-Pedrajas, N.; Castillo, J. A. R. del; Ortiz-Boyer, D. (2009): A cooperative coevolutionary algorithm for instance selection for instance-based learning. Machine Learning, 78(3), pp. 381–420.

[13] Grandchamp, E.; Abadi, M.; Alata, O. (2015: An Hybrid Method for Feature Selection Based on Multiobjective Optimization and Mutual Information. Journal of Informatics and Mathematical Sciences, 7(1), pp. 21–48.

[14] Guyon, I.; Gunn, S.; Nikravesh, M.; Zadeh, L. A. (Eds.). (2006): Feature Extraction: Foundations and Applications. Studies in Fuzziness and Soft Computing, Springer-Verlag, Berlin Heidelberg.
[15] Hilario, M.; Kalousis, A. (2008): Approaches to dimensionality reduction in proteomic biomarker studies. Briefings in Bioinformatics, 9(2), pp. 102–118.
[16] Hira, Z. M.; Gillies, D. F. (2015): A Review of Feature Selection and Feature Extraction Methods Applied on Microarray Data. Advances in Bioinformatics, pp. 1–13.
[17] Jiliang Tang; Salem Alelyani; Huan Liu. (2014): Feature Selection for Classification: A Review. Data Classification, Chapman & Hall/CRC Data Mining and Knowledge Discovery Series, Chapman and Hall/CRC, pp. 37–64.
[18] Jović, A.; Brkić, K.; Bogunović, N. (2015): A review of feature selection methods with applications. 38th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), pp. 1200–1205.
[19] Kashyap, H.; Das, S.; Bhattacharjee, J.; Halder, R.; Goswami, S. (2016): Multi-objective Genetic Algorithm setup for feature subset selection in clustering. 3rd International Conference on Recent Advances in Information Technology (RAIT), pp. 243–247.
[20] Khan, A.; Baig, A. R. (2015): Multi-Objective Feature Subset Selection using Non-dominated Sorting Genetic Algorithm. Journal of Applied Research and Technology, 13(1), pp. 145–159.
[21] Krishnakumar, K. (1990): Micro-Genetic Algorithms For Stationary And Non-Stationary Function Optimization. Intelligent Control and Adaptive Systems, International Society for Optics and Photonics, Philadelphia, PA, United States, pp. 289–297.
[22] Kudo, M.; Sklansky, J. (2000): Comparison of algorithms that select features for pattern classifiers. Pattern Recognition, 33(1), pp. 25–41.
[23] Mistry, K.; Zhang, L.; Neoh, S. C.; Lim, C. P.; Fielding, B. (2017): A Micro-GA Embedded PSO Feature Selection Approach to Intelligent Facial Emotion Recognition. IEEE Transactions on Cybernetics, 47(6), pp. 1496–1509.
[24] Mukhopadhyay, A.; Maulik, U.; Bandyopadhyay, S.; Coello, C. A. C. (2014): Survey of Multiobjective Evolutionary Algorithms for Data Mining: Part I. IEEE Transactions on Evolutionary Computation, 18(1), pp. 4–19.
[25] Olvera-López, J. A.; Carrasco-Ochoa, J. A.; Martínez-Trinidad, J. F.; Kittler, J. (2010): A review of instance selection methods. Artificial Intelligence Review, 34(2), pp. 133–143.
[26] Pappa, G. L.; Freitas, A. A.; Kaestner, C. A. A. (2002): A multiobjective genetic algorithm for attribute selection. Proceeding 4th International Conference on Recent Advances in Soft Computing (RASC), A. Lofti, J. Garibaldi, and R. John, eds., Nottingham Trent University, Nottingham, United Kingdom, pp. 116–121.
[27] Paul, S.; Das, S. (2015): Simultaneous feature selection and weighting – An evolutionary multi-objective optimization approach. Pattern Recognition Letters, 65, pp. 51–59.
[28] Porebski, A.; Vandenbroucke, N.; Macaire, L. (2010): Comparison of feature selection schemes for color texture classification. 2nd International Conference on Image Processing Theory, Tools and Applications, pp. 32–37.
[29] Rathee, S.; Ratnoo, S. (2020): Feature selection using multi-objective CHC genetic algorithm. Procedia Computer Science, International Conference on Computational Intelligence and Data Science, 167, pp. 1656–1664.
[30] Rathee, S.; Ratnoo, S.; Ahuja, J. (2017): Instance Selection using Multi-objective CHC evolutionary algorithm. Proceedings of Third International Conference on ICTCS, Springer, Udaipur, India, pp. 475–484.
[31] Rathee, S.; Ratnoo, S.; Ahuja, J. (2019): Simultaneous Instance and Feature Selection using Multi-objective CHC Algorithm. SSRN Scholarly Paper, Social Science Research Network, Rochester, NY, pp. 1–7.
[32] Ratnoo, S.; Rathee, S.; Ahuja, J. (2018): A Clustering Based Hybrid Approach for Dual Data Reduction. International Journal of Intelligent Engineering Informatics, 6, pp. 468–490.
[33] Saeys, Y.; Inza, I.; Larrañaga, P. (2007): A Review of Feature Selection Techniques in Bioinformatics. Bioinformatics, 23 (19), pp. 2507–2517.
[34] Salappa, A.; Doumpos, M.; Zopounidis, C. (2007): Feature Selection Algorithms in Classification Problems: An Experimental Evaluation. Optimization Methods Software, 22(1), pp. 199–212.
[35] Saroj; Jyoti. (2014): Multi-objective genetic algorithm approach to feature subset optimization. IEEE International Advance Computing Conference (IACC), pp. 544–548.
[36] Senecal, P. K. (2000): Numerical Optimization Using the Gen 4 Micro-genetic Algorithm Code. UNIVERSITY OF WISCONSIN MADISON.
[37] Spolaor, N.; Lorena, A. C.; Lee, H. D. (2010): Use of Multiobjective Genetic Algorithms in Feature Selection. Eleventh Brazilian Symposium on Neural Networks, IEEE Computer Society, Sao Paulo, Brazil, pp. 146–151.
[38] Tan, F., Fu, X.; Zhang, Y.; Bourgeois, A. G. (2008): A genetic algorithm-based method for feature subset selection. Soft Computing, 12(2), pp. 111–120.
[39] Toscano Pulido, G.; Coello Coello, C. A. (2003): The Micro Genetic Algorithm 2: Towards Online Adaptation in Evolutionary Multiobjective Optimization. Evolutionary Multi-Criterion Optimization, Lecture Notes in Computer Science, C. M. Fonseca, P. J. Fleming, E. Zitzler, L. Thiele, and K. Deb, eds., Springer Berlin Heidelberg, pp. 252–266.