Evolutionary Multiobjective Optimization (EMO)

We consider a multi-objective problem of the form:

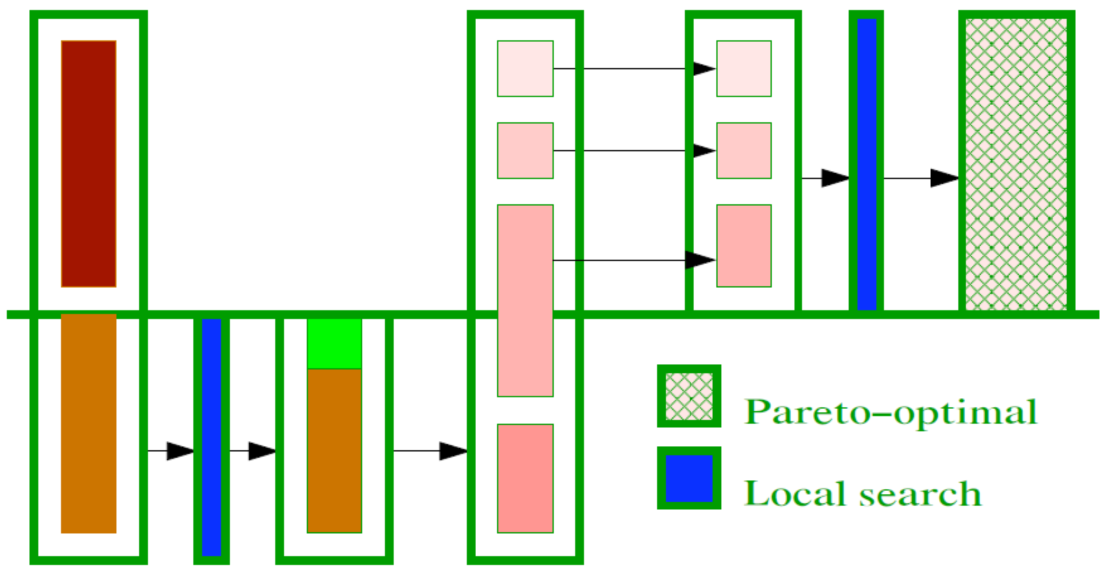
$$\text{minimize}\left(f_1(X), f_2(X), \ldots, f_k(X)\right)$$
$$\text{subject to } X \in S$$

Involving $k \geq 2$ conflicting objectives $f_i : \Re^n \rightarrow \Re$ to be minimized simultaneously. The decision (variable) vectors $X = (x_1, x_2, x_3, \ldots, x_n)^T$ belong to the feasible set S.

Scope of Research:

- Bring together two diverse fields (EMO and MCDM), sharing common objective of solving multiobjective optimization problems.
- Hybrid EMO Algorithms using better scalarizing functions from MCDM.
- Efficient and practically viable EMO algorithms.

Concurrent Hybrid Algorithm



Salient Features:

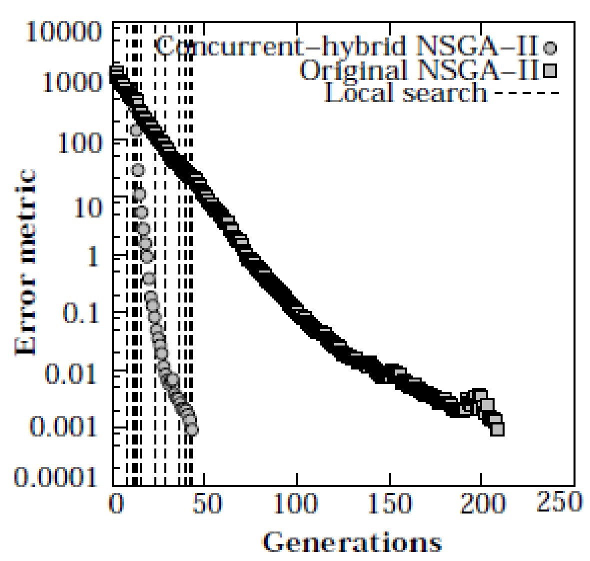
- An efficient concurrent hybrid algorithm proposed.
- Achievement scalarizing function used for scalarization of objectives, as their optima are always Pareto optimal.
- Hybrid algorithms have **Novel termination criteria** based on optimal value of scalarization function.
- A **saw tooth function for local search**, which maintains exploration-exploitation balance.

EMO – NSGA-II

Test Problem	Serial approach			Concurrent approach		
	Best	Median	Worst	Best	Median	Worst
ZDT1	30,083 (0.9289)	31,043 (0.9283)	33,468 (0.9285)	**13,328** (0.9214)	14,518 (0.9285)	16,991 (0.9286)
ZDT2	29,384 (0.6526)	31,760 (0.6530)	32,344 (0.6532)	**1,861** (0.2100)	13,748 (0.6513)	15,716 (0.6510)
ZDT3	33,691 (0.7738)	37,325 (0.7742)	38,545 (0.7742)	**16,595** (0.7155)	20,866 (0.7744)	29,628 (0.7744)
ZDT4	35,006 (0.9274)	54,214 (0.9284)	63,584 (0.9286)	**34,459** (0.9286)	37,724 (0.8982)	43,142 (0.9286)
3-DTLZ1	201,957 (1.664)	252,952 (1.1965)	351,954 (1.1964)	**66,369** (1.1995)	146,506 (1.1931)	290,792 (1.2002)
3-DTLZ2	35,757 (0.8694)	43,722 (0.8813)	70,606 (0.8687)	**26,665** (0.8705)	31,604 (0.8765)	36,006 (0.8803)
4-DTLZ2	69,449 (1.0861)	93,835 (1.0701)	128,794 (1.0750)	**61,028** (1.0960)	74,187 (1.0834)	194,581 (1.0782)

Results:

- Concurrent Algorithm consumes less function evaluations.
- Exact gradient shall further reduce the function evaluations.
- Concurrent-hybrid NSGA-II, converges faster to desired error metric as compared to original NSGA-II.

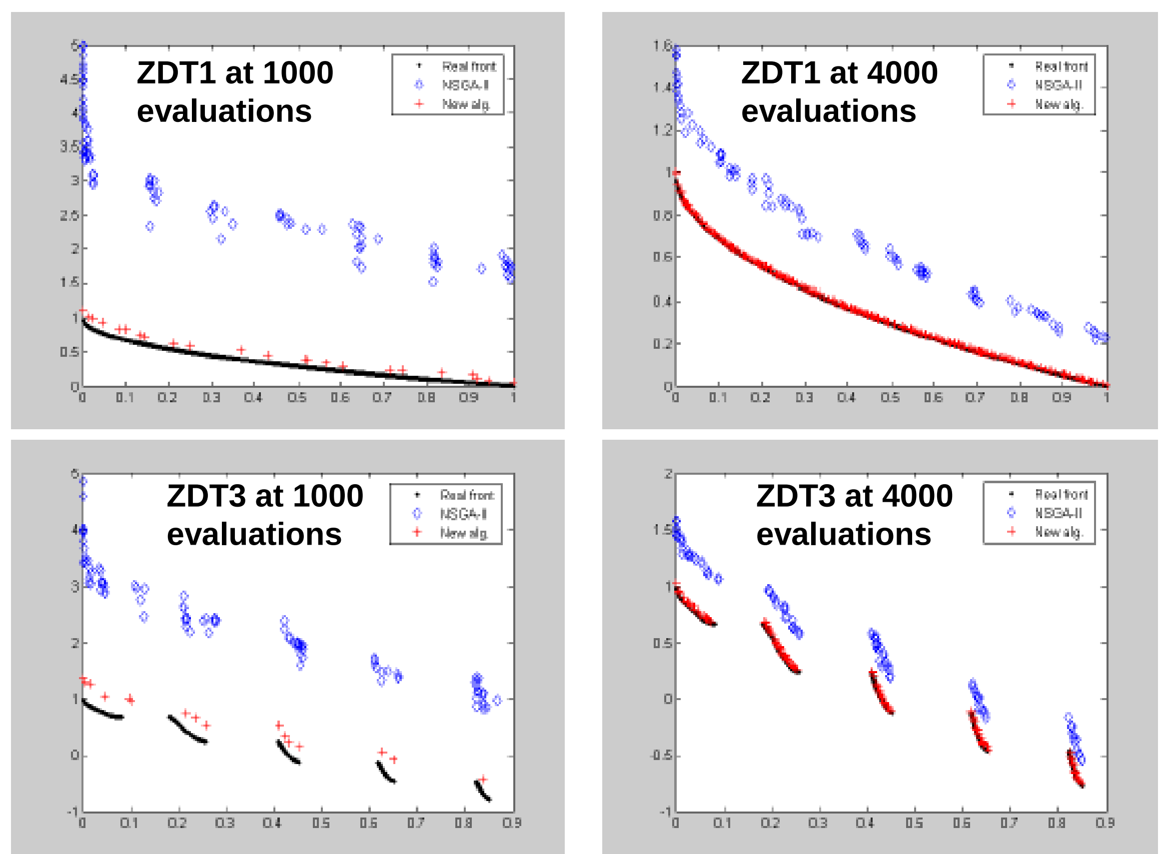


UPS-EMO Algorithm

1. Create initial population.
2. Produce *n* children with randomly selected parents using point generation mechanism of Differential Evolution (DE).
3. Combine current population with child population.
4. Filter dominated solutions away, and use filtered population as current population.
5. If stopping condition is not met, continue to step 2.

Salient Features:

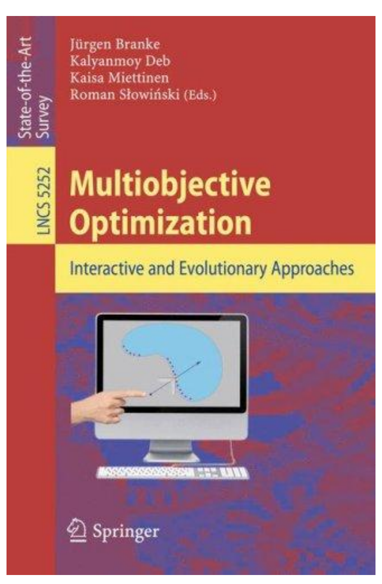
- **Unrestricted Population Size**, (hence the acronym UPS-EMO).
  - Growing population contains all non-dominated solutions found during the optimization.
    - Continuous convergence to the non-dominated set because the population cannot oscillate.
    - Improved efficiency in the beginning of the process (small population converges faster).
    - Better capability to capture the characteristics of the Pareto optimal set (higher number of points in the end).



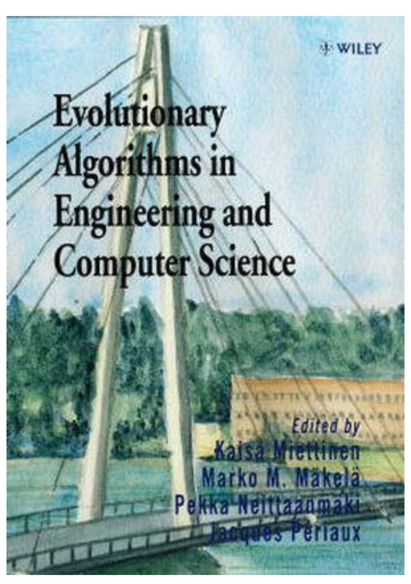
Result:

- A computationally efficient novel EMO algorithm proposed and shown to be efficient on a number of test problems.

Mutiobjective Optimization – Interactive and Evolutionary Approaches



Evoluionary Algorithms in Engineering and Computer Science



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