INNOVATION OF GENETIC ALGORITHM CODE GenA FOR VVER FUEL LOADING OPTIMIZATION

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ABSTRACT

One of the stochastic search techniques - genetic algorithms – was recently used for optimization of arrangement of fuel assemblies (FA) in core of reactors VVER-440 and VVER-1000. Basic algorithm was modified by incorporation of SPEA scheme. Both were enhanced and some results are presented.

1. GENETIC ALGORITHMS AND SPEA

Genetic algorithms (GAs) are search routines based on natural model for evolution of species. In nature, living beings, which are better adapted to their environment, have better chance to survive and produce offspring; thus, given sufficient time, their better-adapted offspring (sharing advantageous trait) prevail over worse adapted competitors, which eventually die-out. There are two basic genetic operators: crossover and mutation operators. Crossover operator requires (at least) two parents to interchange their genetic material to produce a new offspring. On the other hand mutation requires only one 'parent'; it represents random causes that change parent in one or several genes. The crossover operator generally makes smaller changes and can be seen as a local search method, while mutation operator makes bigger changes and is more an exploration method. As in reality, making smaller adjustments means there is smaller chance to fail, but successful adjustment will be probably- at least in one step- only slightly better. Mutation is otherwise high-risk, high-reward approach to solution of problem. A balance between both operators is necessary.

In practice, GAs search from one group (population) of solutions (individuals) to another, in contrast to searching from one solution to another. This approach bears great robustness for optimization tasks; searching is less prone to the premature convergence. In order to add multi-criteria optimization ability we upgraded optimization by incorporating optimization technique, SPEA [1], with concept of Pareto-front based searching. Our recent work in optimization field is described in [2]. Thereinafter we describe some new ways in which we improved used algorithms.

2. SPEA MODIFICATIONS

Pareto optimization means that instead of searching one best solution we seek a set of best so far found compromise solutions among competing variables, fig.1.
Pareto-based search offers several advantages over conventional genetic algorithms or other optimization methods: no weighting parameters, full-area search and great robustness of search. Unfortunately in our case full-area search is not so favorable; full-area search means we try to search for solutions in the whole area, regardless of unreasonably low power peaking/low boron concentration or high power peaking/high boron concentration.
Therefore we made the following adjustment: There is a mechanism in SPEA, which maintains uniform distribution of solutions alongside Pareto-front, which uses distance measurement (metric) among solutions. We modified this metric; now it is "curved". It means that the distance between two points (on plane) is now regarded as distance between two points on the curved surface fig.2. It enables preferring certain area of space of solutions, while, before the projection, homogeneity of the searched plane is still preserved.

3. CROSSOVER OPERATOR

It allows to share good traits of solutions among population of feasible solutions. Originally HTBX operator was used; but over the time the operator proved to be a quite complicated scheme. The main problem was to include other fuel loading constrains. This constrains maintain valid fuel inventory, symmetry of core, forbid placement of fresh fuel assemblies on certain positions and fixate chosen points in core during application of crossover operator. In HTBX this issue was solved by mapping of parent fuel arrays and thereafter by using of assembly reactivity ranking [1]. So we used direct crossover operator, which solves this problem by removing one of the repeated FA randomly and by inserting the missed FA in its place. This approach is more common and allows more flexible implementation of constrains fig.3. HTBX option is still preserved.

4. MUTATION OPERATOR

Mutation operator chooses two random positions and swaps the fuel assemblies with one another. 30deg symmetrical optimization is a bit different; if chosen positions are not diagonal (with regard to 30deg symmetrical positions), then symmetrical positions are also changed. If one position is diagonal and the other is not, then operator ensures the created offspring is also 30deg symmetrical. New types of mutations have been tested, but results are approximately the same. We still investigate this issue.

5. RESULTS

Here we want to show some results from optimization of projected ETE NPP Unit 2, Cycle 4 (reactor type VVER-1000). Calculations were performed by ETE macrocode. Assemblies are without burnable poisons, which are assigned later [3]. Calculations are for fixed cycle length 300 FPD, where we take residual boron concentration, but power peaking from the middle of the cycle is used (because of burnable poisons assignment). Calculations are pursued in 30deg symmetry, for 130 generations with population size of 75 individuals and external set size of 25 individuals.

In fig.4 the map of solutions is shown, and examples of solutions alongside Pareto-front are presented in figs 5-7.

6. CONCLUSIONS

Results from new, upgraded version of GenA, a Pareto-based genetic algorithm program is presented. Results are promising, but more testing and experience with application of the altered way of calculation and of new options are needed.

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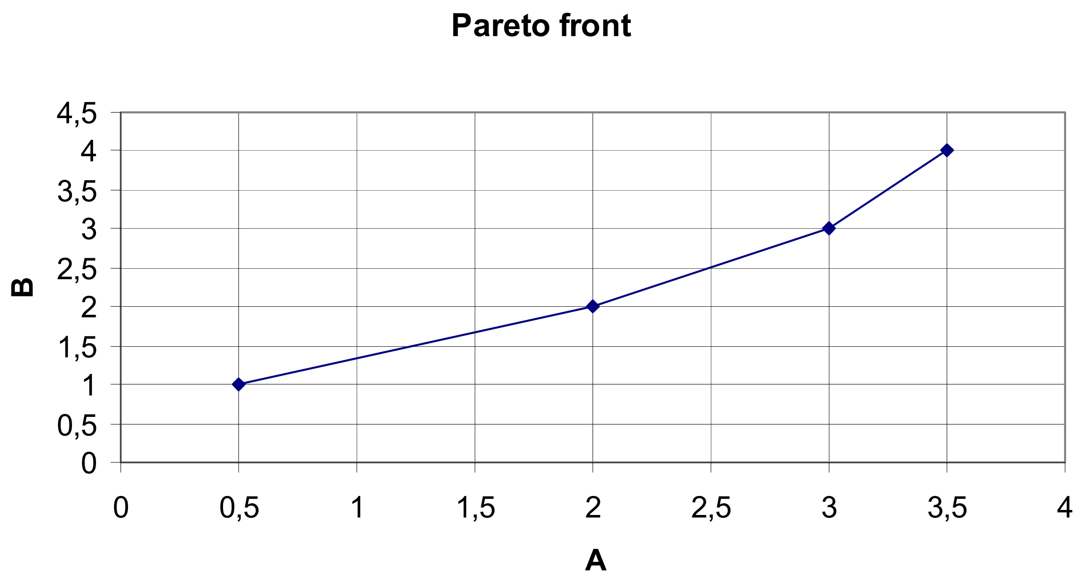

Fig.1 Example of Pareto-front.

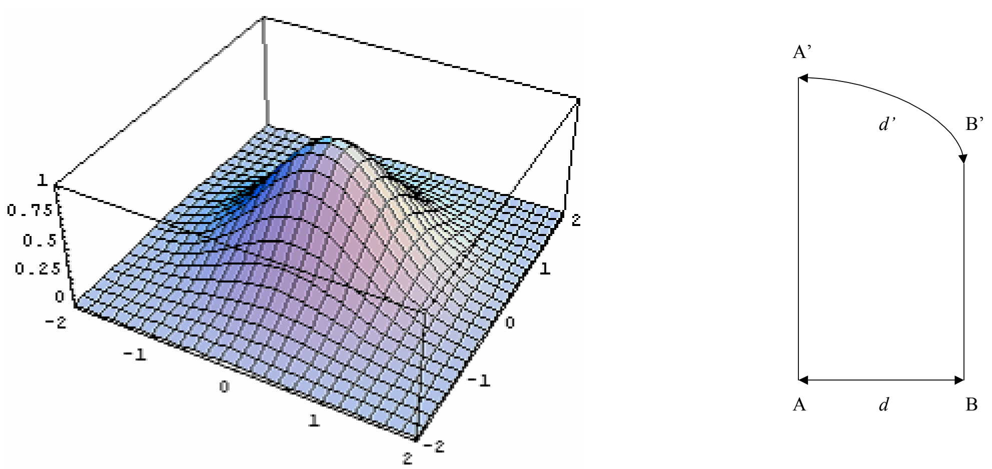

Fig.2 Example of the curvature of the distance metric.

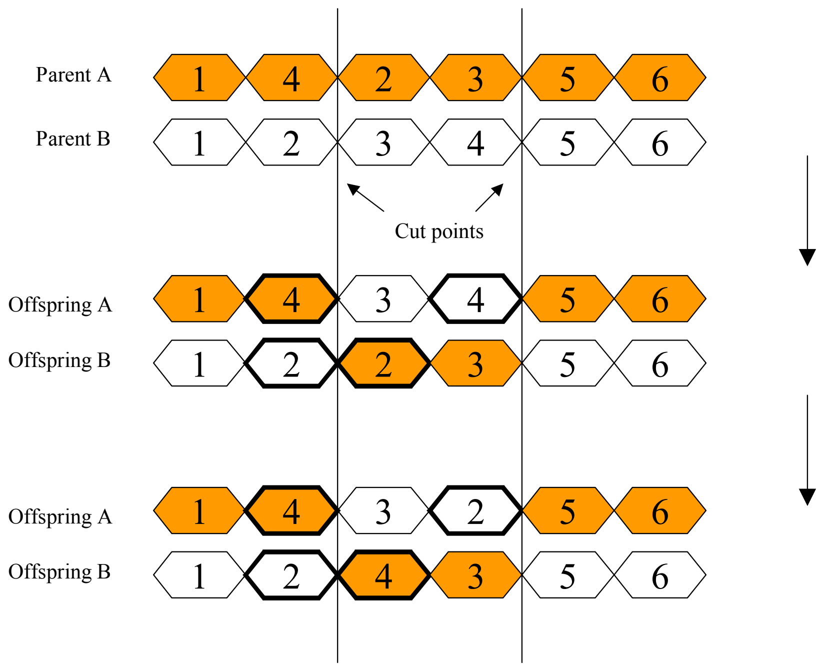

Fig.3 Scheme of the crossover operator.

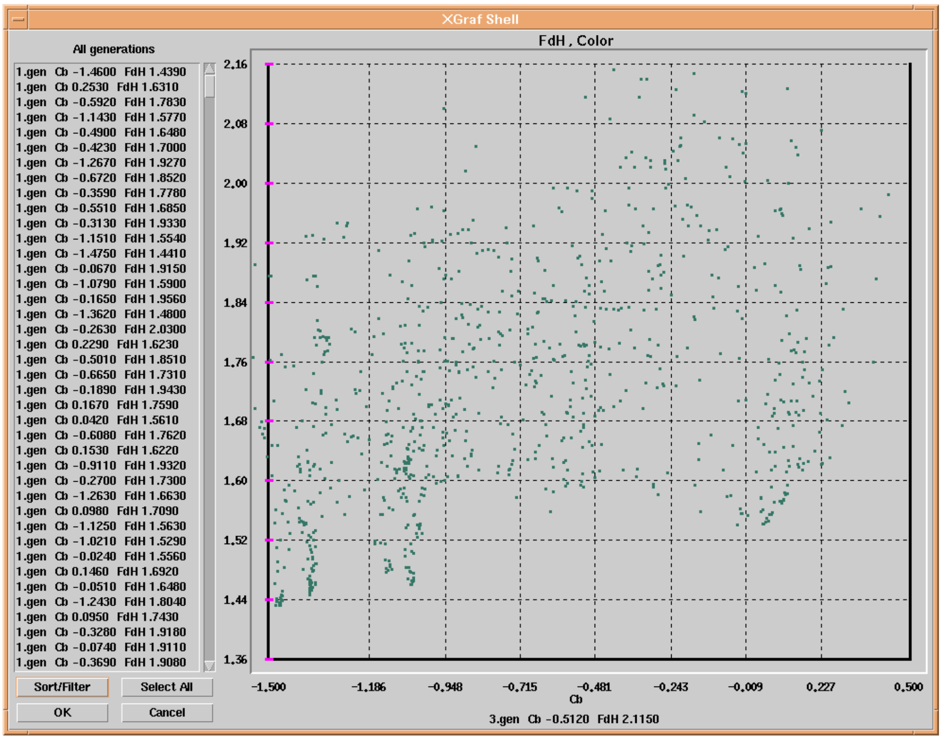

Fig.4 Example of the map of solutions.

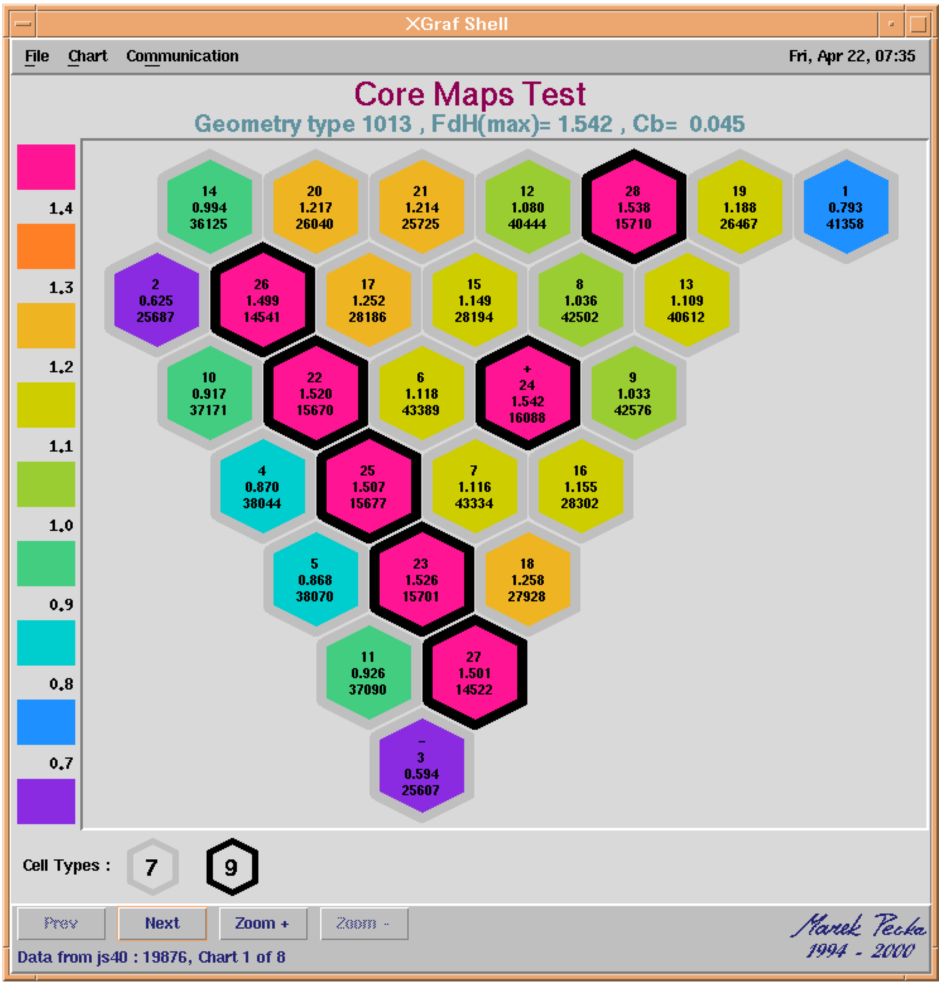

Fig.5 Example of the solution alongside Pareto-front.

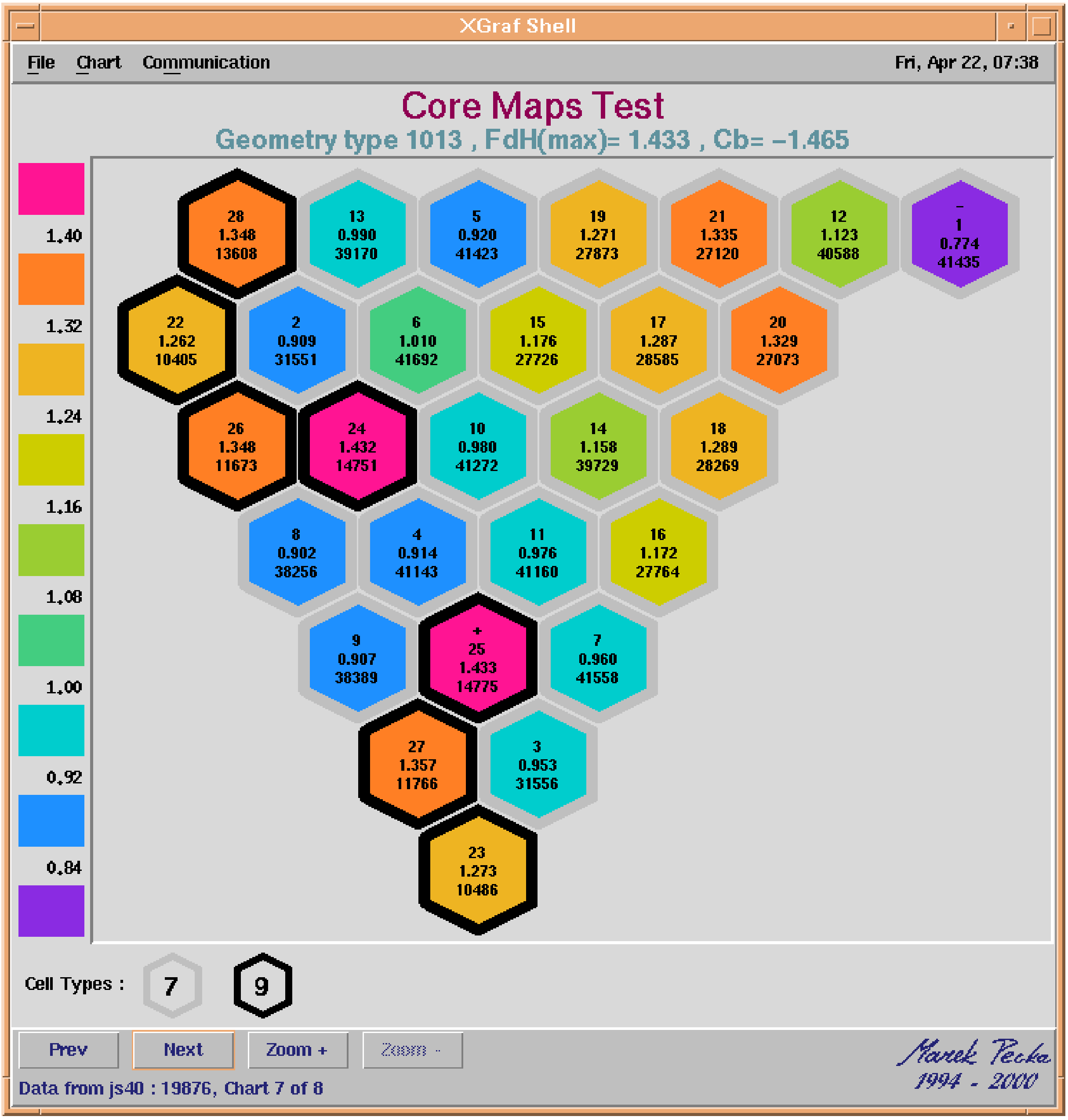

Fig.6 Example of the solution alongside Pareto-front.

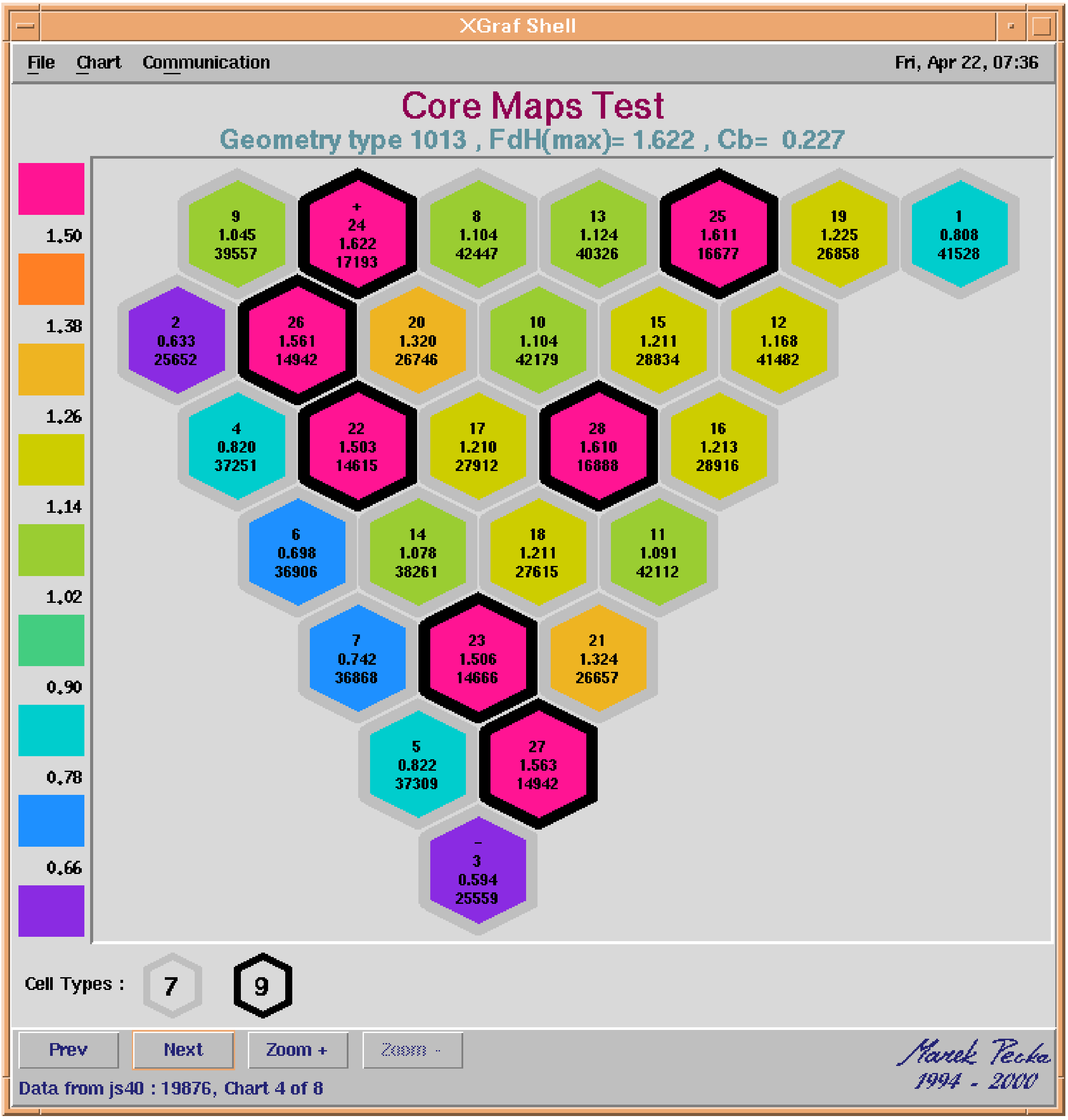

Fig.7 Example of the solution alongside Pareto-front.