Application of the PSO algorithm to the Multi-objective Optimization of insulation elements based on dynamic population size

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Abstract — Most of the existing stochastic optimization algorithms consider fixed number of population members throughout the optimization procedure. This research suggests the use of dynamic population size throughout the optimization PSO algorithm. The results are compared with test functions. The emphasis is on the applicability investigation of the suggested algorithm, which is applied on the real engineering problem. The comparison includes the DE optimization algorithm that is the most common optimization algorithm used in the field of engineering. Both algorithms (PSO and DE) are suitably modified in order to operate with the principle of the optimal Pareto front. The significant element of the presented algorithm is that the population is divided onto local and global optimum search.

I. INTRODUCTION

Particle Swarm optimization method [1] it is a very efficient algorithm and it is applied on many engineering problems. In comparison to the original version, many modifications have been made to the algorithm that has produced many improvements [2], [3]. Also, the PSO algorithm is extended into multiobjective particle swarm MOPSO [4]-[6] on the basis of a non-dominant solution sorting (Pareto concept). Although the PSO algorithm does not contain genetic operators in its fundamentals, it has been proven that the introduction of the mutation is very useful [7]. The presented method enables the enhancement of the solution space. The more recent modifications of the algorithm introduce the dynamic population size throughout the optimization process. A variable [8], [9] or fixed [10] change of the population size during the iteration is possible. The method that includes variable changes of population size enables the change in any iteration. The method with fixed change of population is determined with predefined step of iteration.

Reduction of the population is desired, when the lasting time of the optimization needs to be shortened. However, the efficiency and robustness of the modified algorithm must not change.

II. NUMERICAL MODEL AND OPTIMUM SIGNIFICATION

The research shows different methods, which are used for reduction of the population size. The selected method for reduction is presented on an example of a medium voltage bushing. Bushing is an element that is used to connect switchgear units. The main construction part of the bushing is the body, made of epoxy resin. To fill the space between the body and the contact connection silicon rubber or any similar elastic insulation material can be used (Fig. 1). With the correct combination of materials it is, possible to reach adequately low values of electric field strengths at the boundaries between the dielectrics, thus bringing increased reliability and longer life expectancy for the insulation materials.

Numerical model for electric field calculation consists of parametrically-written model of the bushing (geometry *p*1-*p*5 and materials *p*6-*p*7). It is necessary to perform FEM calculation [11] for each assessment of the objective functions. In the design process there is a condition to satisfy three requirements. The first objective (objective function f_E) evaluates the magnitudes of electric field strength at the boundaries between the dielectrics, the second f_{M1} describes the quality of the first insulation material and the electrical potential at the boundary between both insulation materials, whereas the third function f_{M2} describes the electrical potential on the boundary between the second insulation material and the surrounding medium.

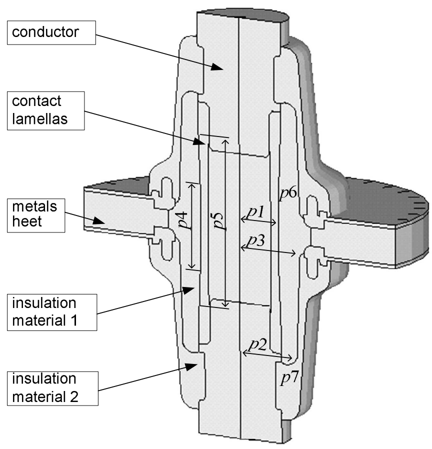

Fig. 1. Model of medium voltage bushing for connecting two switchgear units.

III. DYNAMIC POPULATION SIZE IN THE PSO ALGORITHM

In this paper the optimization procedure considers two approaches for the dynamic population size employed in the multiobjective problem. The first approach is based on weighted sum method and on inclusion of a special procedure of dynamic reduction of population size. The original idea is presented by Brest [10] and claims gradual reduction of the population size by half in each block of a predefined iteration number. This means, that the reduction is not applied throughout all iterations. Fig. 2 shows the example where the population reduction has been carried out four times and the coefficient that defines the reduction is $p_{max} = 4$. In each reduction step the population is reduced in a half in comparison to its former size.

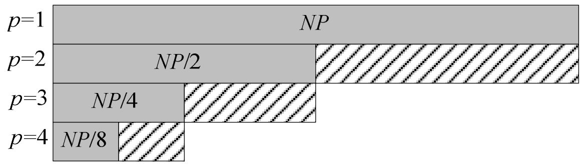

Fig. 2. Shematic presentation of the population reduction.

Full paper contains the improvement of the basic idea whereas the procedure includes the dynamic reduction step. Reduction step is not previously determined, but on the basis of the estimation criterion, which is defined in regards to the optimization procedure.

The specific property of the bushing element model is that all three objectives are conflict to each other; therefore it is possible to solve the multi-objective problem adequately by applying the Pareto concept, which represents the second approach used for multiobjective optimization of the bushing element. The result of the Pareto optimization is the population of different optimal solutions that lay on the so-called Pareto front. The main objective of the dynamic population use in the PSO algorithm is in the local search of the well estimated objective functions and in the global search of the worse estimated objective functions. At the same time, the population reduction is included as well respectively the dynamic population based on crowding distance, which is the main factor for solution dispersion determination.

IV. RESULTS AND CONCLUSION

The results of multi-objective optimization are shown in regards to the two approaches described in the previous section. The convergence of the optimization algorithm according to the weighted sum method is shown in Fig. 3 and set of non-dominated solutions according to all three objective functions (f_E, f_{M1}, f_{M2}) in Fig.4.

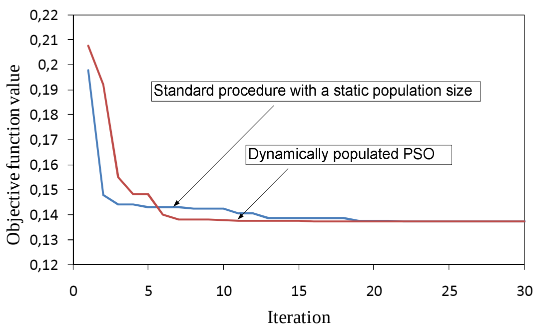

Fig. 3. Convergence of optimization algorithm.

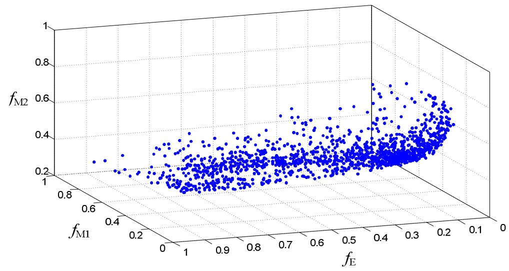

Fig. 4. Pareto optimal solutions according to all three criteria.

The complete results of the optimization process, as well as the description of the dynamic population application for the optimization algorithm, are presented in the full paper. Also, the detailed presentation of the PSO optimization algorithm is given as well as the advantages of the dynamic population, which is the essential part of the algorithm. Objective functions are shown in greater detail. The quality of the Pareto solutions is evaluated with the hypervolume. Modified PSO algorithm is compared to the original PSO algorithm and also with similar DE algorithms [12] in order to prove the usability and improvement.

V. REFERENCES

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