

Various approaches to problems of multicriterion optimization processes of electric power systems

Korovkin Nikolay^{1,2}, Odintsov Mikhail^{1,2},
Belyaev Nikolay^{1,2}

¹Theoretical Electrical Engineering dept. St.Petersburg State
Polytechnical University, Russia
Nikolay.korovkin@gmail.com

Frolov Oleg²

²Joint Stock Company «Scientific and Technical Center of
Unified Power System».
Saint-Petersburg, Russia

Masashi Hayakawa^{3,4}

³Hayakawa Institute
of Seismo Electromagnetics Co. Ltd.,
The Univ. of Electro-Communications (UEC)
Incubation Center

⁴Advanced Wireless Communications Research Center and
Research Station on Seismo Electromagnetics. UEC
Tokyo, Japan

Hayakawa@hi-seismo-em.jp

Abstract— The efficiency of multi-criterion optimization methods for enhancing the efficiency of operating states of electric power systems (EPS) has been studied. On the example of 14-node IEEE-circuit there have been compared Pareto multitudes obtained by two methods. The first one consists in applying the traditional approach of multi-criterion problem solution. The second one creates Pareto multitude with the use of non-dominated sorting algorithm. Has been developed an approach to compare the efficiency of the multi-criterion optimization algorithms. It is shown that with the regard to time-consuming costs the first approach is 10-20 times inferior to the second one. The solution of two-criterion power flow optimization problem of Kolskaya EPS has been performed; a recommendation on the control of operating states of a given EPS has been presented.

Keywords— quality vector criterion; multi-criterion optimization; genetic algorithm; non-dominated sorting; control of operating states of power systems; power flow optimization

I. INTRODUCTION

The optimization of the operating state of EPS examined here, as the solution of real technical tasks is the process of optimization upon quality vector criterion. It shall be reasonable to describe the steady-state operating mode by a series of qualitative and quantitative criteria of its efficiency. Probable sets of these criteria have been studied in [1-3]. The most important task is to develop the methods of optimization task solving upon quality vector criterion.

Classical approaches to the solution of optimization tasks upon quality vector criterion have been considered in details in [3-8]. The approaches are based on the reduction to a single main criterion and its further optimization by applying well developed methods of single-criterion optimization.

The objective of this paper is to consider and to evaluate the probability of success of new method applicability aimed at optimizing the operating states of EPS based on the so-called non-dominated sorting [9,10].

A. Vector criteria

Let us describe the operating state of a power system by a certain vector criterion with each component representing a scalar criterion. The following may represent scalar criteria:

The maximum deviation of voltages in nodes $\max \Delta U_k$ [12]. This criterion defines possible voltage deviations of electric energy receivers from rated values ($\pm 5\%$ for normally admissible deviation and $\pm 10\%$ for maximum admissible deviation).

Criterion, which is close to the first one: $\Sigma \Delta U_k$.

Cross-section power flow – criterion which allows the reaching of the maximum closest value to a given value $\Sigma |P_k - P_{k,rat.}|$ of power transferred via cross-section. A considerably smaller flow shall result in under-utilization of lines while a considerably greater flow shall result in over-current of the line.

A criterion, which is close to that one considered above: $\max(P_k - P_{k,rat.})$.

Active power losses ΔP_n .

Here we do not claim the completeness of scalar criteria set whose the list may be considerably expanded. The above criteria may be affected by changing the parameters of EPS. Among such parameters are the following: FACTS devices, loads, CT ratios of transformers, generator voltage [13].

B. Classical approaches

Classical approaches to solving the problems of multidimensional optimization P_1, P_2 described in [4-8] may be divided into two types.

The main criterion is typical to the first approach. All other criteria shall be understood as secondary and shall play the role of additional constraints in the optimization process. The introduction of additional constraints shall contribute to the degradation of optimization algorithm convergence. The selection of the main criterion conflicts with the terms of a given problem of vector optimization because the vector optimization suggests that several equal or close criteria are available.

A new generalized criterion obtained due to linear or min-max reduction of scalar criteria with normalizing factors is typical for the second approach. The method is sensitive to the selection of normalizing factors.

The final solution of optimization problem upon vector criterion depends on a subjective evaluation of a researcher of the importance of some scalar criteria of the quality. The subjective evaluation of several criteria importance may be partially compensated by applying Pareto optimality.

Pareto optimal solution is the solution from the multitude of admissible solutions where the improvement is impossible within the range of admissible solutions without deterioration of another criterion. Let us introduce the notion of “dominancy”. One solution is dominating the other, if it is better upon one of the criteria at least and is not worse than the second one. The multitude of Pareto optimal solutions forms Pareto multitude. The representation of Pareto multitude in criteria range is called Pareto front.

The optimization problem upon vector criterion is reduced to the sequential solution of two sub-problems: search of the Pareto multitude and selection of a final solution. The problem of final solution selection from the multitude of Pareto effective solutions is not studied in this paper. It should be noted that it would be necessary to maintain the diversity in Pareto front because the set of close solutions does not expand the opportunities for selection.

The notions of dominancy and Pareto front are explained on Fig. 1 for the case of two criteria. The solution A is dominating solutions D_1, D_2, D_3 and is dominated by solutions P_1, P_2 . In their turn solutions P_1, P_2, P_3, P_4 constitute Pareto multitude with the respective Pareto front.

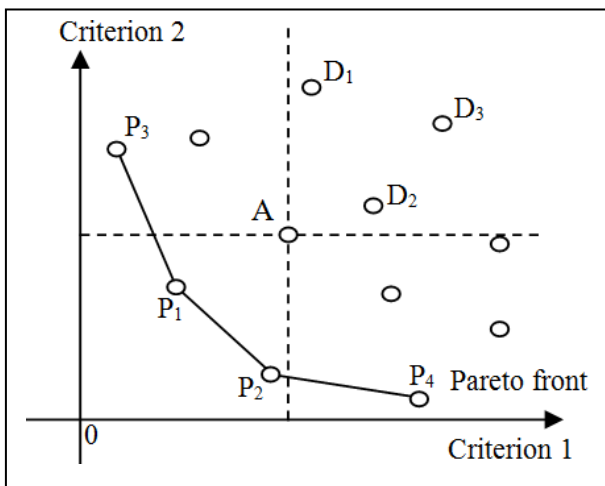


Fig. 1. Pareto front and “dominancy”

Pareto multitude may be formed by minimax or linear reduction methods while using various sets of normalizing constants. The main weakness of applying the reduction method to form Pareto multitude consists in its duration, because to form a representative multitude calculations having a large number of normalizing constant sets are needed.

C. Utilization of nondominant sorting

The main weakness of classical methods consists in difficulties related to Pareto multitude formation after multiple starts of the scalar optimization process with different sets of weight factors.

Starting in 1984 intensive work has been in progress to develop an optimization algorithm upon vector criterion based on evolution algorithms. A brief overview of developed algorithms is presented in [13]. In the genetic algorithm, the selection of the “parent” is done on the basis of comparisons of fitness function values. In the case of single-criterion optimization, the selection of the fitness function is evident while for multi-criterion optimization the problem of appropriate fitness function development became an object of researchers’ attention.

There are two algorithms in [14] that use different ways of specimen comparison. In NSGA (Non-Dominated Sorting Genetic Algorithm) the principle of non-dominated sorting is applied for the selection of a parent during tournament selection. From two specimens one specimen dominating the other one is selected as a parent. There may be another situation when no specimen is dominating (Fig. 1, solutions P_1, P_2, P_3, P_4) the second. Therefore, the notion of Pareto rank is introduced. Index $R=1$ is assigned to solutions making part of the Pareto front. After that all solutions with $R=1$ are eliminated from studies. Other solutions of the multitude making part of the Pareto front, they are assigned with $R=2$ index (see Fig. 2) etc. Then all the solutions are arranged in conformity with their functions, for example, $1/(1+R)$.

The introduction of the notion “rank” does not contribute to solving completely the problem of specimen comparison because the specimens with equal ranks remain non-arranged. Partially it may be compensated by using the notion of scarcity. This notion shall be introduced as metrics to measure the distance between solutions having the same rank. On Fig. 2 the notions of scarcity are illustrated by the example of Manhattan distance when a specimen A is in more sparsed space than another specimen B , because $A_1+A_2 < B_1+B_2$. Among two specimens with equal rank, it shall be reasonable to select as a parent the specimen whose sparsity index is greater. Such an approach shall contribute to uniformly filling the Pareto front. If the specimen is on the boundary of Pareto front, it shall be considered as being in ever sparsed space. Such an approach shall contribute to filling uniformly the Pareto front.

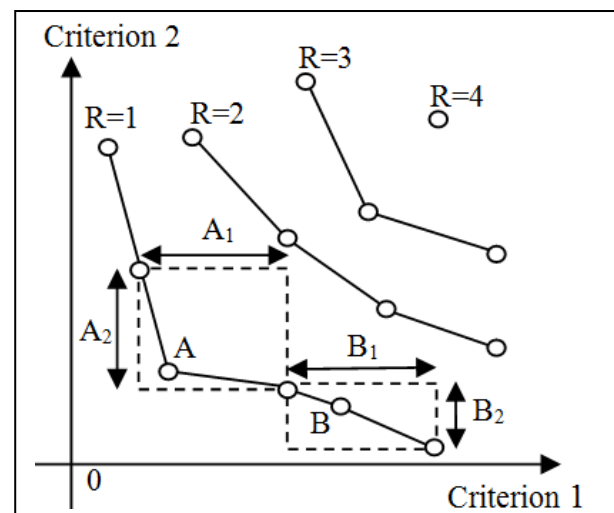


Fig. 2. Rank and sparsity

II. APPLICATION FOR MULTICRITERION OPTIMIZATION MODES OF EPS

A. Method comparison

A considerable interest involves the evaluation of the efficiency of new notion introduction for EPS active and reactive power flow optimization. We have performed on 14-node test circuit IEEE [15] the comparison of NSGA and genetic algorithm that does not use the non-dominated sorting.

For GA there shall be formed several sets of weight factors. For each of them there shall be performed scalar optimization by applying minimax reduction of individual criteria. The best specimens received during each start of single-criterion optimization shall coincide and then from the multitude of solutions Pareto multitude shall be selected.

There shall be formed in NSGA the archive of specimens of primary population. By applying the method of non-dominated sorting the ranking shall be. On the basis of tournament selection, the best specimens shall be selected from the archive. The selected specimens shall create the population of descendants. This population shall be added to the archive and the cycle is to be repeated. To render the archive compact all the specimens with the rank over 2 shall be eliminated.

To test circuit of 14-node system IEEE as variable parameters shall be considered inductances of arms with rated voltage of 220 kV when the range of changes makes 0,3 pu – 1 pu with interval of 0,001 pu, that is equal to the simulation of controllable series compensators installed in given power transmission lines. In this case the number of possible combinations makes $701^7 \approx 8,3$ that renders it impossible to resolve the problem by enumeration. The criteria of quality are the criteria of overall losses (f_1) in arms and maximum relative deviation of voltage versus the rated voltage in circuit nodes (f_2).

The efficiency of algorithms has been compared upon two parameters:

- surface restricted by the Pareto front and straight lines drawn through preably identified points of criteria minimum ($\min f_i$) at the right angle to respective axis O_i at one side, at the other side (minimal surface corresponds to more qualitative Pareto front);
- number of elements making Pareto front (the more are the elements the better).

For studied two-criterion problem, the efficiency of the specified Pareto front has been assessed by the formula:

$$I = \frac{\sum_{i=1}^{n-1} S_i}{S_{\Sigma}} = \frac{\sum_{i=1}^{n-1} (f_1(\bar{x}_{i+1}) - f_1(\bar{x}_i)) \cdot (f_2(\bar{x}_i) - \min f)}{(f_1(\arg(\min f_2)) - \min f) \cdot (f_2(\arg(\min f_1)) - \min f)}$$

The closer I is to zero; the better the way of Pareto front finding. At that if there is another effective solution, which is not dominating the found solutions, the value of I is decreased in the same way as for improving found solutions. The graphical interpretation of efficiency function is shown on Fig. 3.

In Table 1 is shown the efficiency of the found Pareto front and in Table 2 – the number of elements in Pareto multitude for NSGA and GA according to the number of calculations of steady-state modes. A simple calculation of steady-state modes for variable vectors corresponds to a simple calculation of quality criteria. As the genetic algorithm a stochastic optimization

method is used, the result comparison was done on the basis of 100 starts and averaging obtained results.

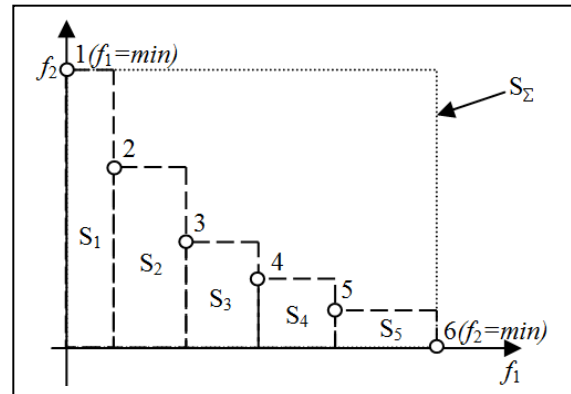


Fig. 3. Assessment of efficiency of numerical search of Pareto front

TABLE I. DEPENDENCE OF PARETO FRONT EFFICIENCY ON THE NUMBER OF CALCULATIONS OF STEADY-STATE MODE

Algorithm	Number of sets of weight factors	Efficiency and rms deviation	Number of steady-state mode calculations						
			100	200	500	1000	2000	5000	10000
NSGA	-	I	0.531	0.412	0.330	0.309	0.292	0.277	0.270
		σ	0.035	0.028	0.011	0.008	0.005	0.003	0.002
GA	5	I	0.522	0.478	0.423	0.417	0.406	0.396	0.392
		σ	0.033	0.026	0.022	0.020	0.017	0.012	0.009
	10	I	0.488	0.459	0.401	0.378	0.363	0.351	0.343
		σ	0.026	0.022	0.014	0.015	0.013	0.011	0.008
	20	I	0.458	0.449	0.406	0.379	0.355	0.334	0.324
		σ	0.019	0.020	0.015	0.012	0.010	0.008	0.007

TABLE II. NUMBER OF ELEMENTS IN PARETO FRONT

Algorithm	Number of sets of weight factors	Number of elements and rms deviation	Number of steady-state mode calculations						
			100	200	500	1000	2000	5000	10000
NSGA	-	I	8	25	57	82	119	200	307
		σ	1.93	4.76	6.69	9.50	12.45	20.64	30.00
GA	5	I	8	11	14	15	14	14	15
		σ	2.10	2.75	2.31	2.17	2.23	2.27	2.43
	10	I	11	15	21	25	27	28	28
		σ	2.48	3.04	3.23	3.57	3.64	3.59	3.97
	20	I	14	16	22	29	38	48	52
		σ	2.77	3.14	4.15	4.63	5.01	5.13	5.05

From shown results, the conclusion may be made that the usage of NSGA for multi-criterion optimization of steady-state modes of power system is more effective method than GA usage. When using NSGA at 500 calculations of steady state modes the results are similar to those received for 5000-10000 calculations with the use of GA. When comparing rms deviations of efficiency function it follows that the stability of obtained results in NSGA exceeds by 1,5 – 2 times that one for 500 calculations and by 3,5 – 4 times for 10000 calculations.

The size of Pareto multitude when using NSGA is also 2,5 – 4 times greater for 5000 calculations and 6-20 times greater for 10000 calculations than when using GA. An rms deviation of Pareto multitude size versus a mean value of Pareto multitude size is also greater than when using GA. That may be explained by the greater size of Pareto multitude. Rms values of deviation reduced to the average value of Pareto multitude size are equal between each other for NSGA and GA.

The advantage of NSGA over GA may be explained by the fact that in the case of GA when optimizing one set of weight factors the solutions that are the best for another set are lost.

B. Real problem

The algorithm of Pareto multitude creation on the basis of non-dominated sorting has been applied for active and reactive power flow optimization of Kolskaya power system (464 nodes and 588 arms at 27 variable parameters). Models obtained on the basis of control measurements of the Russian power system for the year of 2012 were taken as design model.

The criterion of minimizing active power losses in arms has been taken as the first criterion. As a second criterion this one of maximizing the voltage safety factor has been selected (see [16]).

The optimization has been performed due to the change of transformation ratios of autotransformers and set voltage values on generators buses.

The circuit contains 13 nodes with adjustable voltage and 14 transformer arms with adjustable transformation ratios. While performing optimization the technical constraints have been taken into account: range of power change of electric power plants, maximum admissible overflows in controllable cross-sections and level of voltage in circuit nodes. The optimization has been completed when no improvements of Pareto front have been observed during 10 descendants.

On Fig. 4 are shown Pareto multitudes after 200, 500 calculations of steady-state modes and the completion of optimization algorithm upon vector criterion (5940 calculations). Fig 4 shows that a dispatcher controlling the operating state after 500 calculations of target functionals (8-9 seconds) has a sufficient number of versions to improve current operating states. In this case, increasing the number of target functionals calculations Pareto front is improved.

For studied state according to [16] the voltage reserve factor shall not be rated below 0,15. It may be concluded from this that an observed reserve of 0,25-0,3 is excessive and it would be better to exclude this criterion from consideration and to focus on the problem of loss diminution in the circuit.

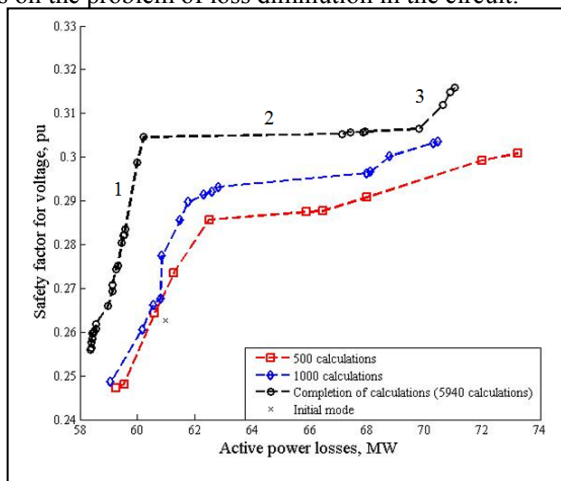


Fig. 4. Assessment of efficiency of numerical search of Pareto front

On Fig. 4 a particular interest may be paid to parts 2 and 3. Here you can observe the break of Pareto front, i.e. a small increase of voltage reserve shall lead to a rapid increase of

losses in the network. On part 1 there is practically a directly proportional dependence between losses and voltage reserve factor. Thus, the most efficient control of power system may be reached at the part 1. The control of part 2 or 3 shall result either in a rapid degradation of one of the parameters or in simultaneous degradation of both parameters. So, you should avoid the parts 2 and 3 when performing the control of power system operating conditions.

III. CONCLUSION

The application of genetic algorithms with probabilities of optimization upon vector criterion is a prospective trend for the optimization of power system operating states. The efficiency of NSGA has been evaluated on the example of 14-node circuit IEEE. The working capacity of the method has been proven on the example of optimization of the circuit of a real power system. The examples of analysis of Pareto front have been given in order to take further solutions.

The main plus of the method of non-dominated sorting is the simplicity of its implementation and the frame of results. A large set of possible solutions may be obtained when optimizing upon vector criterion, the algorithm stability may be increased due to the absence of degenerated population.

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