Paper accepted for presentation at 2009 IEEE Bucharest Power Tech Conference, June 28th - July 2nd, Bucharest, Romania

Critical Consideration of the Suitability of Randomized Optimization Methods: Power System Topology Estimation Problem

Marija Zima-Bočkarjova, *Student Member, IEEE*, Ernst Scholtz, *Member, IEEE*, Mats Larsson, *Member, IEEE*, Göran Andersson, *Fellow, IEEE*

***Abstract*—Many engineering areas are benefiting from the abundance of powerful computing capabilities, which allows for the application of computationally intensive techniques, such as computational intelligence. Such techniques are frequently universal and do not require excessive tailoring for the specific problem. That makes it attractive for wide use, but is however, sometimes, unjustified.**

This paper discusses the necessity to evaluate whether a particular problem is suitable to be addressed using such techniques, for the particular case of combined power system state and topology identification.

***Index Terms*—Randomized optimization, Genetic algorithm, Power system state estimation, Topology, Power Systems.**

I. Introduction

ADVANCES and availability of computational power has encouraged many important technological breakthroughs during past several decades. To mention some of the rapidly developing areas beyond the IT industry itself: the material science, chemical industry, computer-aided design, industrial control are a few examples [1].

Power Systems are nonlinear, large-scale complex systems that are subject to numerous events/phenomena with various physical impacts and time scales. These systems require different modeling and computational techniques, and due to the nonlinear relationships and high-dimensionality of power system processes, power engineering is a promising possible application area for analysis using intensive computations. Furthermore, frequently optimization of such processes results in non-convex, non-smooth problems, where the classical derivative-based methods perform poorly if they can find a solution at all.

A number of derivative-free optimization methods was developed for these types of problems, such as genetic algorithms, simulated annealing, ant colony optimization etc. These methods direct the search toward an optimum based on the collected statistics of the objective-function values combined with a randomized search mechanism. There are many examples of very successful applications [2], [3], [4] of artificial intelligence in power system area encouraging further interest within the community.

It would seem that Power System State Estimation (SE) [5], [6], [7], [8] - a widely used control center tool which synthesizes a real-time power system state from a set of raw redundant measurements through a maximum likelihood approach, could be another promising area for the randomized optimization. Indeed, since the topology of the system is not always known and the performance and reliability is strongly dependent on the validity of the power system model, SE could be formulated as a combinatorial optimization problem. In this case, binary variables could encode possible topologies as well as which measurements to exclude from the consideration as bad data.

A variant of combinatorial-based optimization [7] and the generalized state estimation [9], [10], [11] was successfully implemented as a commercially available software package [12]. This algorithm is based on the branch-and-bound method, i.e., in this case structured enumeration of the possibilities, systematic evaluation of each option varying one parameter at a time. The cost function in this case is the number of wrong measurements and the state estimation verifies bad data presence in the considered measurement sample and the assumed model assumptions (such as switch statuses). The algorithm lists a number of possibilities and converges fast [9] in the reasonable vicinity of the correct solution. The algorithm targets identification of the wrong status of some switches rather than full reconstruction of the substation topology from the ”flat start” and requires knowledge of the substation layout.

Limited redundancy, lack of the substation layout information or large number of switches having unmonitored status may lead to the weak initial point, particularly, at the implementation stage of the state estimator. That shall create a promising niche for such algorithms as tabu search, cross entropy or genetic algorithm.

The major concern, however, regarding the feasibility of the randomized combinatorial optimization application, in case of topology identification, is the behavior of the SE objective function in the neighborhood of the correct topology. Since all the randomized optimization methods are based on the statistics of the objective function evaluations in the search space, the optimization becomes more efficient than the blind random search only in case, when the statistics gives better indication concerning the search direction.

This paper proposes several possible algorithm performance

M. Zima-Bočkarjova and G. Andersson are with ETH Zürich, Physikstrasse 3, CH-8092 Zürich, Switzerland, e-mail: (see http://www.eeh.ee.ethz.ch/psl/).

E. Scholtz is with EPIC Merchant Energy, Houston, TX, USA, e-mail: exscholtz@emelp.com.

M. Larsson is with ABB Corporate Research, Baden-Dättwill, Switzerland, e-mail: mats.larsson@ch.abb.com.

978-1-4244-2235-7/09/$25.00

indicators for the evaluation the suitability of randomized optimization methods for a general problem, while considering the combined state and topology estimation problem as a particular example.

II. Background on the Randomized Optimization

A. Genetic Algorithm

GA encodes each point in a solution space into a bit string and associates it with an objective function or fitness value. Comparing to more traditional approach, as for example the derivative-based optimization algorithms, instead of a single point at each iteration GA keeps set of points as population that evolves constantly towards a better overall fitness using the operators below [1]:

- **Evaluation:** evaluation of each individual solution contained in the population
- **Selection:** chooses individual solutions from the population that shall be a basis for the next iteration (offspring)
- **Crossover:** random recombination of the parameters of the selected individual solutions
- **Mutation:** randomized change of the selected individual solution.

The iteration of the algorithm proceeds as follows. First, elite individuals are selected from the population based on their overall ranking. Repetitive tournaments between four randomly selected individuals define parents of the crossover and mutation children. The crossover rate defines the number of crossover children, as a fraction to non-elite population. The rest of the population is formed by selected parents that may mutate with the probability defined by the mutation rate.

Consequently, the overall characteristics of the population improve when nearing optimal solutions, while allowing a certain degree of random diversity.

B. Cross-Entropy Algorithm

The Cross-Entropy (CE) method [13] is a population based combinatorial or continuous optimization method belonging to the class of randomized algorithms. The optimization according to this method consists of three major steps:

- Generate a number of random solution vectors according to the specified mechanism
- Evaluate the solutions
- Update the parameters of the random mechanism to produce a better next set of solutions.

Thus, similarly to genetic algorithm it operates with the set of solution vectors (population). Unlike GA, CE uses statistics of the whole population rather than individual solutions, to produce the next population - the offsprings. In contrast to GA, the generation of the offspring is more straightforward: it is based on the bit presence statistics in the successful individuals. The quantile defines how many fitter individuals are considered to be successful. The next generation is produced by sampling from the obtained statistical model. The iterative process stops, when each of the bits show either 0 or 100% presence statistics. CE does not involve such operations as mutation and crossover. The justification and derivation of the algorithm can be found in [13], [3], [14].

Instead of the immediate probability vector update, as above, the update of the probability vector can be done with some learning rate:

$$P^k = LR \times P_{gen} + P^{k-1} \times (1 - LR) \tag{1}$$

where P^k is the probability vector to be used for the next generation sampling, P^{k-1} is the probability vector used for the current generation sampling, P_{gen} is the probability vector of the bit success computed from the current generation.

The pseudo code of the algorithm, is:

```
% define size of population,
SizeOfPopulation = 20

% quantile and initial probability = 0.5
Quantile = 4
P = 0.5*ones(length_genome, SizeOfPopulation)

while probability of each bit <> 0 or 1

  % generate population
  population = ...
  rand(length_genome, SizeOfPopulation) < P

  % evaluate
  Evaluation = evaluate(population)

  % compute probability for the next sample
  Sorted_Evaluation = ...
  sort(Evaluation, "descending")
  gamma = Sorted_Evaluation(Quantile)
  loop for each bit j in genome
     P(j) = (number of ...
     best individuals'evaluations >
     gamma coinciding with bit value = 1) /...
     (total number of best individuals >gamma)
  end
end
```

Several other evolutionary algorithms could also be considered for this problem, namely Population-Based Incremental Learning (PBIL) [15], Evolutionary Strategies, Covariance Matrix Adaptation Evolution Strategy [16]. However, the performance of all these randomized algorithms is dependent (in a similar way) on the statistics of the values of the objective function during the search.

C. Performance Measures

Specifically, for the evaluation of the application feasibility of the genetic algorithm the question to answer is: are the fitter (w.r.t. a certain criteria) parents more likely to produce target offspring?

To direct the search towards an optimum, GA employs selection followed by two variation or reproduction mechanisms: mutation and crossover.

Let us first address mutation, and evaluate whether fitter solutions are more likely to produce optimal offspring. We only consider one bit mutation, which has a much higher probability to occur compared to two or more bit mutation. The probability that any solution produces an optimal solution through mutation can be computed, as:

$$P_{mutated} = \frac{1}{N}\frac{N_1}{C_N}, \tag{2}$$

where N_1 is the size of one bit neighborhood of the optimal solution, C_N is the total number of all combinations, N is the number of bits.

In other terms, this $P_{mutated}$ is defined as probability of selecting one of N_1 solutions out of all the possibilities coinciding with the mutation of the "appropriate" bit.

On the other hand, the probability that elite solutions, i.e. solutions with superior fitness, would mutate to an optimal solution can be computed, as:

$$P_{mutated\ elite} = \frac{1}{N}\frac{N_{1elite}}{C_E}, \tag{3}$$

where N_{1elite} is the number of elite solutions, which form one bit neighborhood of the optimal solution, C_E is the number of all the elite solutions. This probability would, naturally, depend on the level of elitism and the optimum solution sought.

To preserve the simplicity and without loss of the conclusiveness, we neglected the necessity to consider the Bernoulli scheme [17] in the derivations, which shall be applied if mutation or crossover rate specifies several parents.

Similarly to mutation, assuming a one-point crossover mechanism, the probabilities of creating the targeted offspring by any two parents can be defined, as follows:

$$P_{crossover} = \frac{1}{N}\sum_{1=1}^{N}\frac{C_i C_{N-i}}{C_N^2}, \tag{4}$$

where C_i and C_{N-i} are the number of solutions with first i-bits and last $N-i$ bits corresponding to the correct solution, respectively.

An expression for the probability of the targeted offspring creation by the crossover mechanism from two elite parents can be derived in a similar way as (3).

For the rational application of the genetic algorithm, following these indices, one should expect at least:

$$P_{mutated} < P_{mutated\ elite} \tag{5}$$

$$P_{crossover} < P_{crossover\ elite}. \tag{6}$$

In comparison, for the random search method the probability of finding an optimal solution at each iteration is $\frac{1}{C_N}$ and the expected number of computations to reach the optimum is $\frac{1}{2}C_N$.

III. Topology Optimization for the State Estimation

The majority of implemented state estimators (SE) rely on the bus-branch transmission system model equivalaneced by the topology processor from the detailed physical level model i.e. including switches and the status measurements of the switches (Fig. 1). The switch status information is known to be very unreliable [8] or frequently not even available to the control center (albeit it might be available at the substation level [18]). Subsequently when assumed switch statuses are wrong, the topology processor will produce an erroneous model. As this may lead to a wrongly estimated state that endangers the system security, it would be desirable to preserve the information regarding the possible topologies and to verify it by SE.

Let us first review traditional power system state estimation. SE involves mapping the states x to measurements z with measurement errors e:

$$z_i - h_i(x) = e$$
$$x = (\theta_1\theta_2\ldots\theta_n U_1\ldots U_n)^T \tag{7}$$

where $h(x)$, known as the *measurement function*, relates the system state vector x containing voltage angles and magnitudes to the measured quantities - voltage magnitudes U_i, bus power injections P_i, Q_i, branch power flows P_{ij}, Q_{ij}.

The measurement errors are assumed stochastic with a Gaussian probability distribution, zero mean and mutual independence. Therefore, equation (7) can be solved for the most likely values of the state variables based on the given redundant measurements.

Since the measurement error expectation values have been assumed to be zero, the most likely state will result in a minimum of the following objective function [5], [8]:

$$J = \sum_{i=1}^{m} W_{ii}\left[z_i - h_i(x)\right]^2. \tag{8}$$

The weights W_{ii} are commonly taken as being inversely proportional to the measurement error variance $W_{ii} = 1/\sigma_i^2$.

The minimum of J can be determined using the first order optimality conditions $g(x) = \frac{\partial J(x)}{\partial x} = 0$. Expanding $g(x)$ in Taylor series around $x^{(k)}$ and neglecting the higher order terms, we obtain:

$$g(x^{(k)}) + \frac{\partial g(x^{(k)})}{\partial x}(x - x^{(k)}) = 0. \tag{9}$$

Thus, the Gauss-Newton iterative solution scheme [17] can be employed to find x satisfying (9). Proceeding with rearrangements leads to the formulation known as *Normal equations*:

$$G(x^k)\Delta x^{(k+1)} = H^T(x^{(k)})\cdot W\cdot[z - h(x^{(k)})], \tag{10}$$

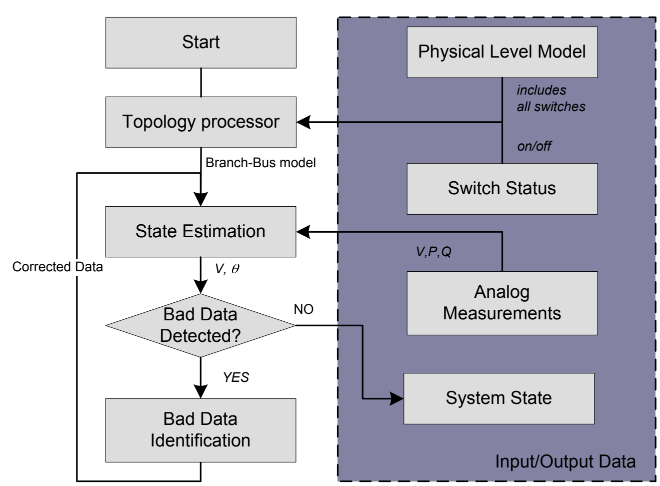


Fig. 1. Influence of the wrong topology on the classical state estimation and bad data detection technique

where

- $G(x) = \frac{\partial^2 J(x)}{\partial x^2} = H^T(x) \cdot W \cdot H(x)$ is gain matrix
- $\Delta x^{(k+1)}$ is the update of the solution at iteration k, so $x^{(k+1)} = x^{(k)} + \Delta x^{(k+1)}$
- $H(x) = \frac{\partial h(x)}{\partial x}$ is measurement Jacobian.

Solving equation (10) for $\Delta x^{(k+1)}$ and iterating until the required accuracy ε is reached, i.e. $\Delta x^{(k+1)} < \varepsilon$, one will obtain the solution of SE.

The topology information, such as whether the branch is connected to one or the other busbar within the substation, can be encoded by the binary vector t into the measurement Jacobian $H(x)$ and the measurement function $h(x)$. The nested optimization problem can be then formulated:

$$\min_t \min_x J, \tag{11}$$

where for every candidate topology t an optimal state x is obtained by (10).

Besides, several experiments were performed with different estimators, such as least absolute value or only injection residuals considered. The results of these test were similar to the described below.

IV. Simulations and Results

A. Power System Model

The performance of the algorithms was tested on the example of the 5-bus (or more precisely in this case, substations) system. The detailed physical level model including switches at substations 1 and 2 is shown in Fig. 2 and its' single line diagram of bus-branch representation is in Fig. 3.

It is assumed that the statuses of the section breaker at the substation 1 and the substation 2 are not known, i.e. it is not clear whether the busbars are split or not. Moreover, the line connections to the busbars at these substations are not known. Thus, a number of possibilities for the topologies can be defined.

These combinations are encoded by a $4{+}4$ bit-strings, since each of the substations has 4 connected lines. In such a bit-string, one would denote connection of the particular line to busbars B as 1, while 0 means the that line is connected to busbars A:

$$t_i = \begin{cases} 0 & \text{if connected to A} \\ 1 & \text{if connected to B.} \end{cases} \tag{12}$$

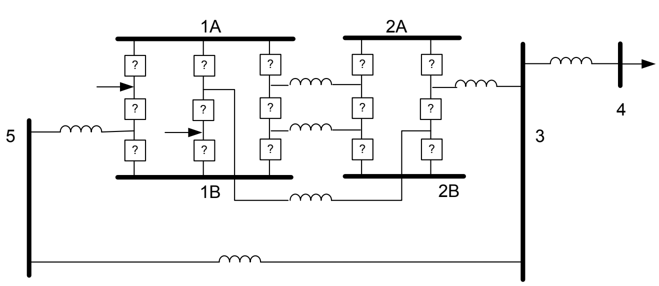


Fig. 2. Physical level model of the test system, explicit modeling of the switches at substation 1 and 2.

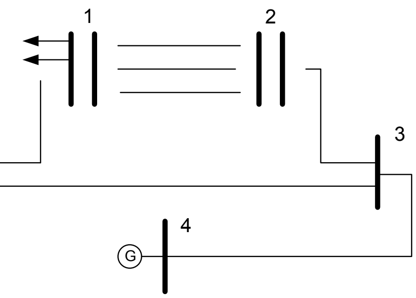


Fig. 3. Bus-branch equivalent of the test system.

For example, the combination 0001 0100 determines, that the first three connections are coming to busbar 1A, while the forth to 1B. For the substation 2, the second connection is closed on busbar 2B and the other three connections 1, 3, 4 to busbars 2A. If the busbar injections are excluded from the measurement set, it naturally follows that the combination 0000 is equivalent to 1111 and the section breaker is closed.

B. Statistics of the objective function

The characteristics of the state estimation objective function versus distance of the topology from the correct one are shown in Fig. 4- 5. Indeed, distance implies if one, two or more bits of the encoding are wrong. The comparison of the objective function statistics for various distances has been performed for a number of randomly chosen topologies and the results presented in Fig. 4-5 appear to be representative.

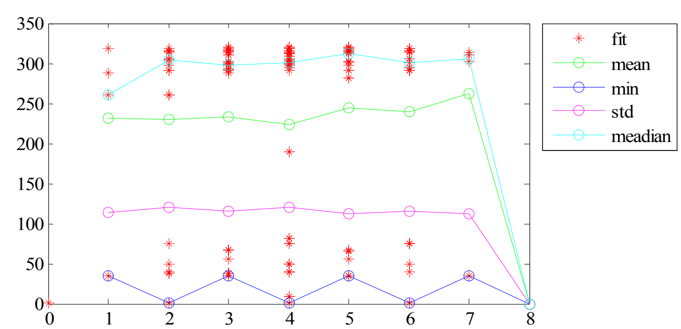


Fig. 4. Characteristics of the objective function vs distance to the optimum, the optimal topology is 0001 0011.

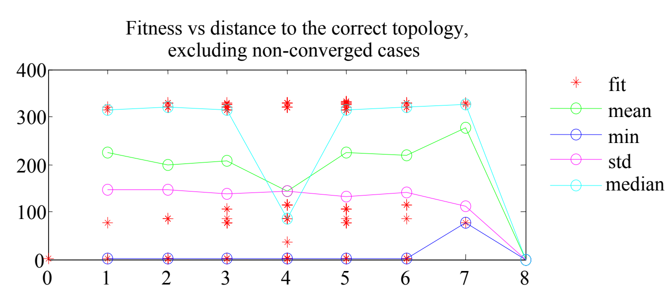


Fig. 5. Characteristics of the objective function vs distance to the optimum, the optimal topology is 0100 0101.

The improvement of the average, median or best solution, when approaching the correct topology can hardly be observed. Removal of the non-convergent cases from the consideration does not change the overall picture, as well as replacing equivalent all-ones with all-zeroes (or opposite) encodings in order to avoid distortion of the statistics.

C. Performance of the GA

Performance of the GA was studied applying indices (3), (4) for different levels of the elitism and the several different topologies. The probability of creation the optimal offspring among elite solutions, as in Fig. 6 is slightly higher in some of the cases, but no general rule can be derived. The probabilities are generally in the same order.

Similar results were obtained for the probabilities of the optimal solution creation by crossover among elite and any parents. The probability grows only for very high levels of elitism, which are difficult to obtain.

Fig. 7 shows number of the solutions versus value the objective function distinguishing the potential parents for the crossover and the other solutions, the last column corresponds to non-convergent cases. It can be observed that there are no more parents in the elite range that non-parent and simultaneously, there are many parents with the high objective function value (non-convergent cases).

Matlab's GA toolbox [19] was used in the simulations in Fig. 8-10. Some additional algorithm tuning options would be possible in self-developed code, for example, preservation of the uniqueness among elite solutions. However, it is conjectured that the obtained results are quite indicative.

Fig. 8-10 show genealogy and improvement of the objective value, for different size of the population, mutation and the crossover rates and different optimal topologies. The elitism defines number of best solutions to be kept for the next generation, tournament size is the number of competing solutions for the reproduction, crossover rate is the part of the non-elite population to be reproduced by crossover and the mutation is the probability of mutation in the remaining offspring.

Fig. 8 and Fig. 9 (a) exploits relatively large tournament size, then most of the solutions are originating from elite in contrast to Fig. 9 (b) and Fig. 10. Higher randomization, i.e. smaller elite, smaller crossover rate as in Fig. 8 (b) generally, show better results. Two further studies for different topologies are shown in Fig. 10 and exhibit similar properties.

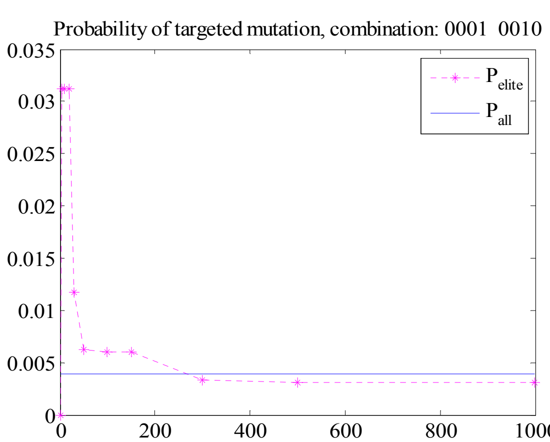


Fig. 6. Comparison of the probabilities of creation the optimal solution by mutation among elite and any solutions, optimal topology 0001 0010.

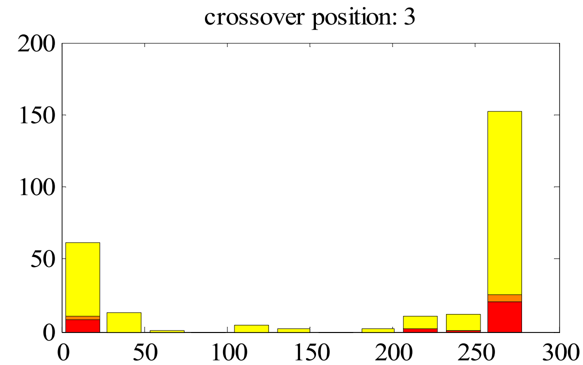


Fig. 7. Distribution of the SE objective function of the potential parents in the 1-7 crossover positions, optimal topology 0010 0100.

In many cases, GA finds a good solution within few iterations. However, frequently non-sufficient variety of the population prevents the algorithm to develop from the local optimum Fig. 9 (b). In that case the level of crossover is increased and the tournament size is decreased, in order to achieve higher diversity, which shows an improvement.

The results demonstrate that GA performance does not show advantage over random search for this problem, that should in average find the optimal solution after 128 evaluations.

D. Performance of the Cross-Entropy method

CE with the 100% probability learning rate suffers from the premature convergence to non-optimal solution. The convergence criterion is a discovery of the optimal solution. Table I summarizes results for other learning rates, sample sizes and several combinations.

TABLE I
STATISTICS OF THE CROSS ENTROPY METHOD PERFORMANCE

Combination	Learning Rate	Sample Size	Nr. of SE performed (average of 5 trials)
0001 0011	0.1	20	168
	0.2	20	676 (> 1000)
	0.2	40	480 (> 1000)
0010 0100	0.1	20	96
	0.1	30	168
	0.2	40	120
0100 0101	0.1	20	712
	0.2	20	192
	0.2	40	136

If at least in one of five trials the optimum was not reached within 50 iterations or 1000 SE evaluations, the indication > 1000 is given in brackets.

Clearly, the larger size of the sample the smaller number of iterations is needed to find the optimum. In the extreme case, when the population size is 2^8, the optimum should be discovered in the first iteration. In general, CE shows poorer performance when compared to a random search.

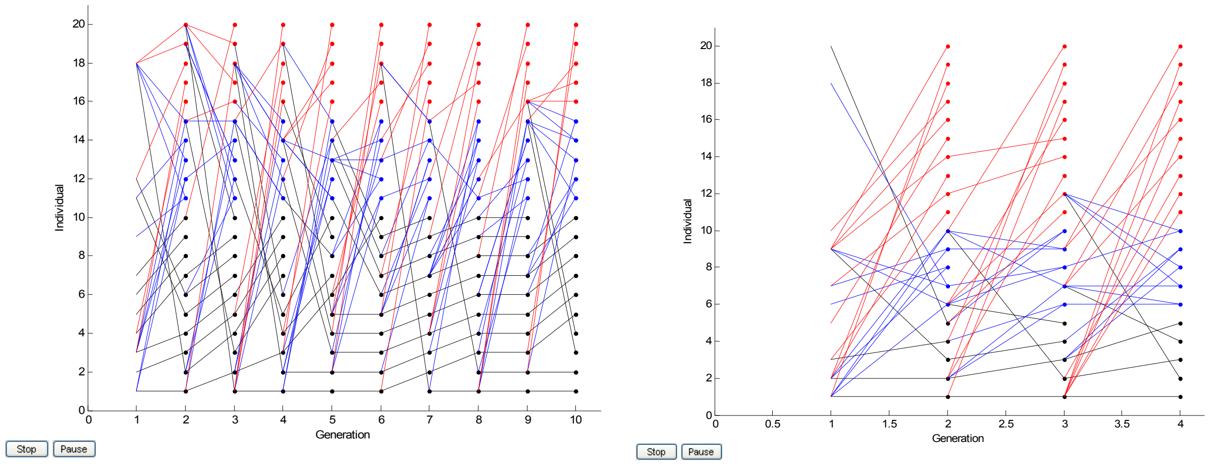


Fig. 8. Evolution of the GA populations. The optimal solution 0001 0010, is reached in 10 and 4 iterations. Black - elite children, red - mutation, blue crossover. Tournament size - 4. (a) Elitism - 10, Crossover - 0.5, Mutation - 0.8; (b) Elitism - 5, Crossover - 0.3, Mutation - 0.5;

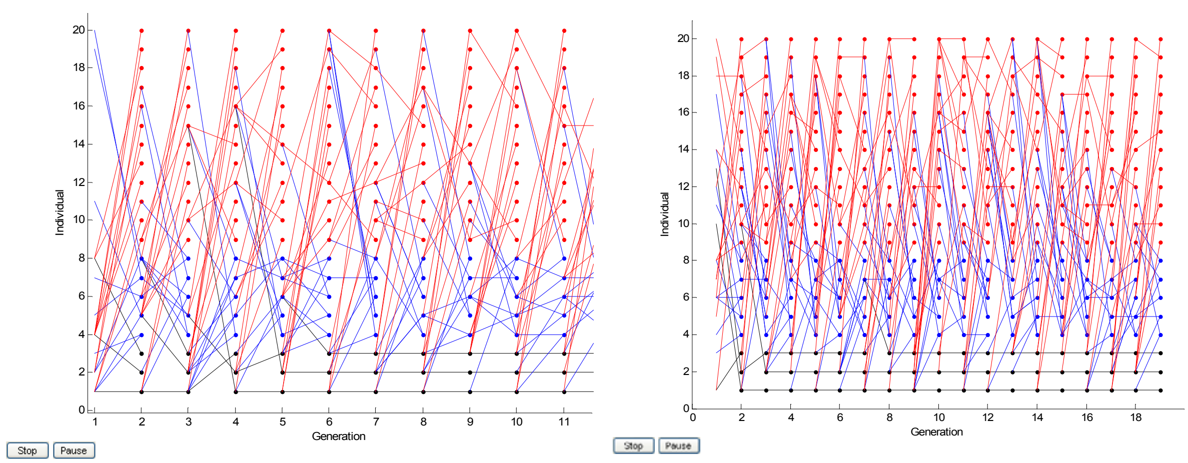


Fig. 9. Evolution of the populations by GA. The optimal solution 0100 0101 is reached in 12 and 19 iterations. Black - elite children, red - mutation, blue crossover. Elitism - 3, Crossover - 0.3, Mutation - 0.9; (a) tournament size 4; (b) tournament size 2.

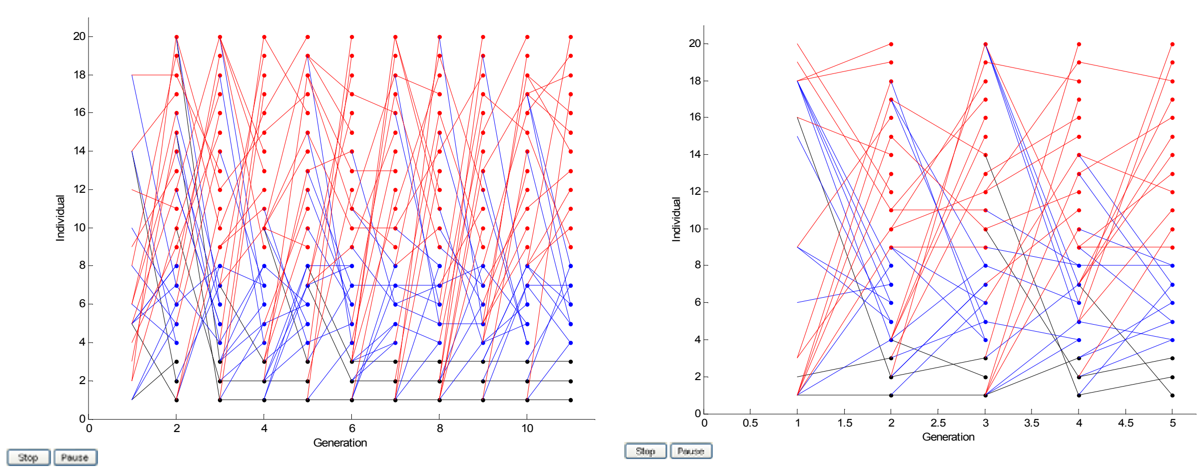


Fig. 10. Evolution of the populations by GA. The final solution reached 11 and 5 iterations. Black - elite children, red - mutation, blue crossover. Elitism - 3 Crossover - 0.3, Mutation - 0.8, tournament size 2. Optimal combination (a) 0001 0011; (b) 0010 0100.

V. Conclusions

Randomized optimization can be a powerful method, particularly suited for the non-convex problems with multiple or local optima. However, it is necessary to evaluate expected performance of the method and the suitability to the particular problem.

The indices proposed in this paper seem to be indicative. For example, studying the results obtained while addressing the topology identification problem, it was demonstrated that the randomized combinatorial optimization algorithms are not well suited for the problem at hand.

Acknowledgments

The authors gratefully acknowledge fruitful discussions with Reynaldo F. Nuqui from ABB Corporate Research and Magnus L. Johansson from the ABB Network Management and the financial support of ABB.

References

[1] J. R. Jang, C. Sun, and E. Mizutani, *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*, US ed ed. Prentice Hall, Sep. 1997.

[2] L. Wehenkel, T. V. Cutsem, and M. Ribbens-Pavella, "An artificial intelligence framework for online transient stability assessment of power systems," *Power Systems, IEEE Transactions on*, vol. 4, no. 2, pp. 789–800, 1989.

[3] D. Ernst, M. Glavic, G. Stan, S. Mannor, and L. Wehenkel, "The cross-entropy method for power system combinatorial optimization problems," in *Power Tech, 2007 IEEE Lausanne*, 2007, pp. 1290–1295.

[4] V. Neimane, "Distribution network planning based on statistical load modeling applying genetic algorithms and Monte-Carlo simulations," in *Power Tech Proceedings, 2001 IEEE Porto*, vol. 3, 2001, p. 5 pp. vol.3.

[5] F. Schweppe and J. Wildes, "Power system Static-State estimation, part I: exact model," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-89, no. 1, pp. 120–125, 1970.

[6] F. Schweppe and D. Rom, "Power system Static-State estimation, part II: approximate model," *power apparatus and systems, ieee transactions on*, vol. PAS-89, no. 1, pp. 125–130, 1970.

[7] A. Monticelli, *State Estimation in Electric Power Systems*, 1999.

[8] A. Abur and A. G. Exposito, *Power System State Estimation*, 2004.

[9] N. Vempati, C. Silva, O. Alsac, and B. Stott, "Topology estimation," in *Power Engineering Society General Meeting, 2005. IEEE*, 2005, pp. 806–810 Vol. 1.

[10] O. Alsac, N. Vempati, B. Stott, and A. Monticelli, "Generalized state estimation [power systems]," in *Power Industry Computer Applications., 1997. 20th International Conference on*, 1997, pp. 90–96.

[11] ——, "Generalized state estimation," *Power Systems, IEEE Transactions on*, vol. 13, no. 3, pp. 1069–1075, 1998.

[12] "Topaz is nexants sophisticated topology estimation tool, developed to overcome the vulnerability to topology errors that traditional energy management system state estimators have to bad input status data." [Online]. Available: http://www.nexant.com/products/pns_topaz.html

[13] R. Y. Rubinstein, D. P. Kroese, and D. P. Kroese, *The Cross-entropy Method*, 2004.

[14] P.-T. de Boer, D. P.Kroese, S. Mannor, and R. Y. Rubinstein, "A tutorial on the cross entropy method," in *http://iew3.technion.ac.il/CE/files/Misc/tutorial.pdf*, 1997.

[15] S. Baluja, "Population-Based incremental learning: A method for integrating genetic search based function optimization and competitive learning," Carnegie Mellon University, Tech. Rep., 1994.

[16] "Nikolaus Hansen, The CMA Evolution Strategy: A Tutorial, January 18, 2009." http://www.lri.fr/ hansen/cmatutorial.pdf. [Online]. Available: http://www.lri.fr/ hansen/cmatutorial.pdf

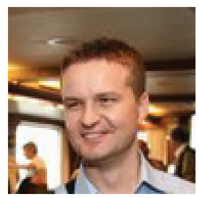
[17] G. A. Korn and T. M. Korn, *Mathematical Handbook for Scientists and Engineers*, 2nd ed. McGraw-Hill Companies, Jun. 1967.

[18] M. Kezunovic, T. Djokic, and T. Kostic, "Robust topology determination based on additional substation data from IEDs," in *Power Tech, 2005 IEEE Russia*, 2005, pp. 1–6.

[19] "Matlab and genetic algorithm and direct search toolbox are mathworks products are covered by one or more patents." [Online]. Available: http://www.mathworks.com/products/gads/

VI. Biographies

Marija Zima graduated from the Riga Technical University, Latvia in 2002. She obtained her PhD from the same university in 2007. In 2000-2005 she was a planning engineer at the National power utility Latvenergo. In 2005 she started the Ph.D studies at ETH Zürich.



Ernst Scholtz received his B.Eng. in Electrical Engineering and his M.Eng in Electronic Engineering from the University of Pretoria, South Africa in 1997 and 1999 respectively, and his Ph.D. degree from the Massachusetts Institute of Technology in the Department of Electrical Engineering and Computer Science in 2004. He was a Principal Scientist at ABB US Corporate Research, in Raleigh, NC from 2004 to 2008. Currently he is a Senior Analyst with EPIC Merchant Energy in Houston, TX. His interests are in the areas of systems, control, and finance theory with a focus on applications in power systems, and industrial processes.

Mats Larsson (M'99) received his Master's degree (Computer Science and Engineering), Licentiate (Industrial Automation), and PhD (Industrial Automation) Degrees from Lund University, Sweden in 1993, 1997 and 2001, respectively. Since 2001 he has been employed by Corporate Research, ABB Switzerland. He is a Principal scientist responsible for the research and development of phasor measurement applications and wide-area stability controls for power systems. His research interests includes power system stability and applications of optimal control and system identification in power systems.

Göran Andersson (M'86, SM'91. F'97) was born in Malmö, Sweden. He obtained his M.S. and Ph.D. degree from the University of Lund in 1975 and 1980, respectively. In 1980 he joined ASEA:s, now ABB, HVDC division in Ludvika, Sweden, and in 1986 he was appointed full professor in electric power systems at the Royal Institute of Technology (KTH), Stockholm, Sweden. Since 2000 he is full professor in electric power systems at the Swiss Federal Institute of Technology (ETH), Zürich, where he heads the powers systems laboratory. His research interests are in power system analysis and control, in particular power systems dynamics and issues involving HVDC and other power electronics based equipment. He is a member of the Royal Swedish Academy of Engineering Sciences and Royal Swedish Academy of Sciences and a Fellow of IEEE.