Comparison of Metaheuristic Algorithms for Simulation Based OPF Computation

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Abstract

Electric power grid operation being an ever challenging scientific field is faced with a high variety of optimization problems. Since the future vision of so called smart grids causes higher complexity and new requirements to these problems, sophisticated investigation in suitable optimization algorithms is essential. Here, metaheuristic optimization strategies are proven to be suitable for high dimensional multimodal problems, and are capable of computing good solutions for hard problems in reasonable time. Therefore, a simulation- based optimization approach is introduced forming a highly applicable framework for testing the suitability of metaheuristic algorithms to practical optimization problems in power grid operation. Different algorithms will be experimentally compared to each other based on Optimal Power Flow computation to the standardized IEEE 30-Bus testcase.

1. Introduction

Since electric power grids are said to be not only one of the oldest, but also the most complex machinery in the world, they are faced with a high variety of optimization problems. Most of these problems are being investigated since power grids exist, but are still central points of interest in power systems analysis and research due to their ever changing nature. To name just a few, the Economic Dispatch (EC) respectively Optimal Power Flow (OPF) problem [1] play an important role in power system operation since their aim is to find optimal operation points to satisfy power load with minimal financial costs. Another highly investigated problem is the unit commitment (UC) problem which tries to decide whether to assign a supply unit to the grid or not [1]. Thus, UC is a discrete optimization problem, while EC and OPF are continuous ones. Various other optimization problems exist as well like different kinds of layout problems, for instance the optimal placement of FACTS- devices. What is important to mention about these problems is that they are highly nonlinear and multimodal, thus finding accurate algorithms for solving them robustly is a hard task.

Nowadays, power grid operation and the corresponding optimization problems get more complex rapidly, since electric grids all over the world are faced with the revolution from analogue power grids to intelligent ones, the so called smart grids. Considering the impact of this revolution on the resulting optimization problems in power systems, highly complex and high dimensional problems will have to be solved.

Metaheuristic optimization strategies can deal with these new problems since they are able to handle high dimensionality and are also proven to be applicated successfully in this field.

In the last couple of years, beside deterministic optimization methods [2,3], metaheuristic algorithms have been investigated with respect to different practical optimization problems, also applied to power systems [4,5,7]. One major lack of such investigations is that they only consider a single specific algorithm in order to solve one concrete practical optimization problem. Since there exist a high variety of these algorithms, comparing different metaheuristic strategies when applying them to optimization problems in power systems would be important in order to investigate their suitability for future technologies. Here, the simulation- based optimization approach realizes a sophisticated framework for these investigations.

This framework as described in [8] is realized as a composition of HeuristicLab [9,10,11], a generic framework for metaheuristic optimization, and the Matlab- toolbox “PSAT” [12], and is used for evaluating metaheuristic optimization methods for power systems. In order to guarantee universality of the optimization solutions, the optimal power flow problem is being solved with respect to the standardized IEEE 30- bus testcase, which is the base problem for later comparisons.

Coming from this problem, the OPF is computed using different metaheuristic optimization techniques implemented in HeuristicLab, like Genetic Algorithms or Evolution Strategy. For each algorithm, searching for optimal parameter- settings is essential, since the choice of parameter- values is crucial to the reachable best solution quality. In the end, the used algorithms are compared to each other with a specific view to best achieved solution and computation metrics. This comparison leads to conclusions about the suitability of various metaheuristic optimization algorithms in solving practical power system problems. Additionally, the simulation- based optimization approach is being introduced as sophisticated approach for investigations in metaheuristic power system optimization.

2. The Simulation-Based Approach

As introduced in [8] the main idea of simulation based optimization is the application of simulation for computing the fitness- values subject to the solution generated by a metaheuristic optimization algorithm. Concerning the satisfaction of constraints, the central concept is the use of a penalty function as proposed in [14] as a measure of violation of constraints, which is added to the cost function and thus minimized simultaneously. The processflow is visualised in figure 1.

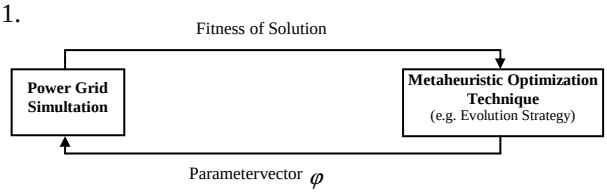

Figure 1: Processflow

This approach is now ported to the OPF problem, which is one of the most important optimization problems in power grid operation, being highly nonlinear and multimodal, with increasing dimensionality in future smart electric grids.

3. Setting up experiments

The Optimal Power Flow Problem

The Optimal Power Flow problem can be stated as finding active power configurations for supplying units in a power grid in order to supply power demand with optimal costs:

Minimize some cost- function

$$F(P_G),$$

subject to the constraints

$$\sum g(P_G) = 0$$

$$\sum h(P_G) \leq 0,$$

where $F(P_G)$ covers the fuel cost of a solution, that has to be minimized. The optimization problem is restricted by a set of equality and inequality constraints, where the equality constraint ensures the satisfaction of the power balance of a solution.

$$\sum_{j=1}^{J} P_G - P_{load} - P_{loss} = 0$$

with P_G as the vector of power outputs of all generators and thus the parameter vector φ as candidate solution , defined as:

$$P_G = [P_{G1}, ..., P_{Gj}].$$

P_{loss} ,as the sum of power losses over all transmission lines L in the system, can be calculated depending on P_G and P_{load} by solving the load flow equations, using for instance Newton- Raphson method. P_{load} is the given power demand specified by the power grid.

The set of inequality constraints includes lower and upper bounds for variables to assure stable operation, for instance the generation capacity (active and reactive) of each generator, that is restricted to a certain range

$$P_{G\,j}^{\min} \leq P_{Gj} \leq P_{G\,j}^{\max}, \; Q_{G\,j}^{\min} \leq Q_{Gj} \leq Q_{G\,j}^{\max}$$

j = 1,…,J,

and the upper limit of the power flow through transmission lines S_l

$$S_l \leq S_l^{\max}, \; l = 1,\ldots,L.$$

J… total number of generators

L… total number of transmission lines

Feasibility of a solution and satisfaction of constraints

In order to ensure that finally found (near-) optimal solutions are feasible, the satisfaction of constraints has to be guaranteed. Here, the equality constraint describing power balance does not have to be considered directly during the optimization process. Since, when computing the fitness of n power outputs of generation units with simulation by solving the power flow equations, only n-1 power values can be determined before, the nth value is specified by the power flow algorithm in order to meet the power balance. Thus, the solution vector P_G only consists of n-1 power values and the power balance satisfaction does not have to be considered when generating a solution. All the other defined constraints have to be considered using a penalty function as defined in [14]. Here, an unfeasible solution is getting penalized by increasing its fitness relative to the degree of violation of certain constraints.

This so defined OPF problem will now be ported to a realistic power grid scenario, namely the IEEE 30 Bus testcase specified in [13].

The Testcase

Since optimization problems are a highly investigated field in power system research, there exist several standardized test models for experimental evaluation of proposed algorithms. Within these standardized models, the IEEE 30 Bus test case is a multiply used power grid model for OPF computation, used for instance by [7,13].

Beside this standardized model, in order to formulate the complete OPF- problem, the generation costs and capacities of generation units have to be defined and are taken from [13]:

Bus Nr	Cost Coefficients			P_G min - max	Q_G min - max
	a	b	c	[MW]	[MVAR]
1	0.00375	2	0	50 - 200	-20 - 250
2	0.0175	1.75	0	20 - 80	-20 - 100

5	0.0625	1	0	15 - 50	-15 - 80
8	0.00834	3.25	0	10 - 35	-15 - 60
11	0.025	3	0	10 - 30	-10 - 50
13	0.025	3	0	12 - 40	-15 - 60

Table 1: Fuel Costs

The corresponding fitness of a solution is computed by summing up fuel costs for all supply units, which are specified by the polynomial function:

$$F_{Pj} = a_j x^2 + b_j x + c_j$$

Algorithms and their configurations

The major concern of this paper is the introduction of the simulation based optimization approach as highly applicable framework for evaluation of metaheuristic algorithms in the case of OPF computation. Therefore, three different algorithms are compared exemplarily, namely Evolution Strategy (ES), Genetic Algorithm (GA) and Offspring Selection Genetic Algorithm (OSGA) as proposed by Affenzeller et al in [15], all implemented in the generic heuristic optimization framework HeuristicLab.

Generally, in order to ensure comparability of results, all experimental optimization runs are limited to 10000 evaluated solutions. This relatively low number is valid since OPF- solutions for this 30 Bus test case known from literature can be reached within a relatively low amount of generations, also stated in [7].

For each of these algorithms, two different configurations are finally compared defined as following:

Mutator	NormalAllPositions Manipulator
Recombinator	AverageCrossover
Configuration 1 ES	
Children	20
Population Size	5
Comma ES	True
ParentsPerChild (ρ)	2
Configuration 2 ES	
Children	100
Population Size	20
Comma ES	True
ParentsPerChild (ρ)	2
Configuration 1 GA	
Population Size	100
Mutation Probability	5%
Configuration 2 GA	
Population Size	100
Mutation Probability	5%
Configuration 1 OSGA	
Population Size	100
Selected Parents	20
Mutation Probability	5%
Configuration 2 OSGA	
Population Size	20
Selected Parents	10
Mutation Probability	5%

Table 2: Algorithm Parameters

For the three different optimization methods, recombination and mutation- operators are equal, as well as population sizes are uniform in order to ensure comparable results.

The naming of the parameters is compatible with the naming in HeuristicLab. All parameters that are not mentioned now are defined by their standard- settings in HeuristicLab.

4. Results

In Order to come over stochasticity of computed results, optimization runs are performed 10 times per configuration. The achieved results are visualized in figure 2:

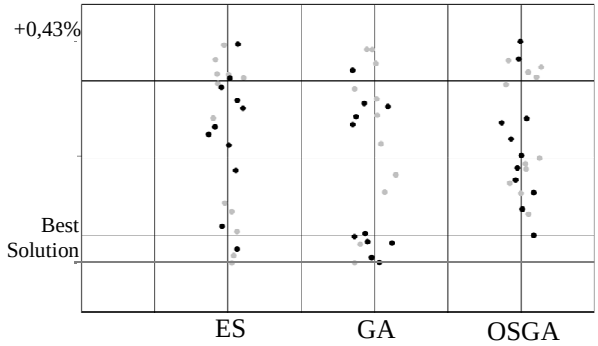

Figure 2: Solutions

Using the huge visualization features of HeuristicLab, the distributions of achieved qualities can easily be shown. Here, for each algorithm, optimization runs with configuration 1 are indicated with grey bubbles, configuration 2 runs with black bubbles. Obviously, no clear pattern can be identified that shows whether low or high population sizes lead to better results for the used problem. Additionally, the relative difference of achieved quality of the worst solution to the best is 0,43%.

The best solutions for each algorithm are shown in table 3:

	ES	GA	OSGA
P1	162,26	163,27	160,75
P2	47,23	43,9	49,4
P5	20,7	21,76	21,35
P8	12,1	13,28	10,75
P11	10	10	10,
P13	40	40	40
Costs	735,45	735,37	735,79
Losses	8,88	8,8	8,85

Table 3: Best Solutions

The best solution has been achieved with a genetic algorithm, but as shown above, the margin between the best solutions is low.

For the application of the OPF computation, time consumption is very important for applying it to electric power grid operation (mostly more important than reaching the global optimal solution). Exemplarily shown in Figure 3 (OSGA, configuration 2), for the given IEEE 30 bus OPF problem, with around 20 generations a reasonable solution could have been achieved. Comparable convergence is given for the other algorithms too.

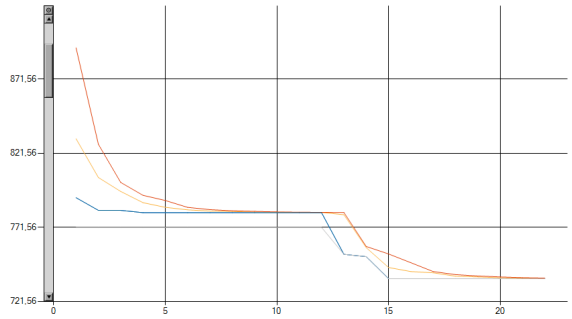

Figure 3: Convergence

5. Conclusions

Finally, a simulation-based optimization approach has been proposed that forms a highly usable generic framework for optimization when being aggregated with an appropriate simulation tool. Consisting of HeuristicLab and PSAT, this framework has been used for evaluation of different metaheuristic methods in order to solve the OPF for the IEEE 30 bus testcase. Using this exemplary problem, its usability has been proven for further investigations in metaheuristic algorithms which are capable of matching future optimization tasks in electric power grid operation.

What is important for future investigations in order to ensure robustness of tested algorithms, they have to be applicated to different test scenarios. Here, the various standardized IEEE test cases with different complexities form a sophisticated base for experiments. Thanks to the simulation based approach, performing experiments with different power grid models only needs of defining them in the simulation software. The generic tool HeuristicLab can be used for optimization without further mathematical effort. Further, it is easy-to-use graphical interface provides various techniques enabling exhaustive analysis of performed optimization runs.

Acknowledgments

This project was supported by the program Regionale Wettbewerbsfähigkeit OÖ 2010-2013, which is financed by the European Regional Development Fund and the Government of Upper Austria.

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