Single- and multi-objective parameter optimization in a tool for designing PV-diesel-battery systems

Arjun Brück, Silvan Faßbender, Eberhard Waffenschmidt

Cologne Institute for Renewable Energy (CIRE), Cologne University of Applied Sciences
Betzdorfer Str. 2, 50679 Cologne, Germany
Corresponding author: silvan.fassbender@th-koeln.de

***Abstract*—In many isolated off-grid areas diesel generators are the common way of providing electricity. The high energy cost and CO2 emissions might be reduced by implementing PV plants with an attached battery storage into the micro-grid. However, the correct dimensioning of both PV and battery storage is crucial. Using a MATLAB/Simulink tool based on previous work, such PV-Diesel systems can be calculated for variable storage capacity, PV sizing and dispatch strategies. To find a preferably efficient optimization method in MATLAB, a genetic and a simplex algorithm are compared. Optimization objectives were low levelized cost of electricity (LCOE) or carbon dioxide (CO_2) emissions, by sizing photovoltaics and battery of the system. The specific algorithms were chosen since they don't rely on derivatives as the Simulink calculation is discrete and non-linear. It is shown that the simplex algorithm converges within a couple of minutes and quiet faster than the genetic algorithm. Furthermore, a multi-objective optimization is implemented using an epsilon-constraint method. The user is able to identify appropriate dimensioning with emphasis on different targets by calculating distinct pareto optimal solutions.**

I. Introduction

Many people in remote areas are living without access to the public power grid. In these regions, often diesel generators are used for supplying electricity. In Africa, the number of people without access to electricity as well as the usage of diesel generators is actually growing due to the growth of population [1]. Because fuel is expensive, it might be difficult to transport to far-off locations and causes emissions, it is desirable to reduce the fuel consumption in these setups. This can be done by extending the micro-grid with PV modules and batteries especially in locations with high sun irradiation. A bigger dimensioning of the PV and battery systems increases the energy yield from the sun, reduces fuel consumption and CO_2-emissions but will also require bigger investment costs. To plan a system before realization, a Matlab/Simulink tool was developed by [2], which simulates hybrid-PV-diesel systems for a certain installed power of PV modules and a certain battery capacity. Since there are two entry parameters and several possible, contradictory objectives it is too extensive for the user of the tool to find a desirable configuration manually. Therefore, pareto optimal solutions are used on the tool to find the number of PV modules and batteries that fit the preference of the user best, regarding the specifics of the situation. This paper aims to determine a time-saving solution for the optimization of the PV and battery size for PV-diesel-systems. Thereby, multi-objective optimization shall be visualized using a pareto front, letting the later tool user decide the weighting between objectives.

II. Simulation

In previous work, a MATLAB/Simulink tool was created to design PV-Diesel systems. The tool is based on advanced models for PV, diesel generators and optionally a battery. For the PV the double diode model is used to achieve a higher accuracy of PV power. The model is able to consider technical data of real PV modules, which are accessible in a data base. The battery model by shepherd indicates the battery state depending of its terminal voltage and experimentally measured discharge curves. This paper, a lead acid battery is implemented. For the diesel generator, a self-made model was used to consider the load step behavior. Additional fuel consumption is determined for load steps higher than 50Load and Irradiation are based on imported profiles in increments of 15 minutes over one year. For each time increment, the system is balanced using a certain dispatch strategy. In this paper, a dispatch strategy is used which balances the residual load with the battery in the first priority. A diesel generator is not started until the battery is discharged. In addition, the battery relieves running generators in order to ensure operation at a certain minimum load. Thus, fluctuations of the PV plant are reasonably shared among diesel generator and battery. Finally, this simulation environment is implemented in a tool to variate the design of PV and battery size. You can read more details about the tool and simulation environment in the paper by Faßbender and Waffenschmidt [2].

III. Optimization

Most optimization algorithms use derivative methods for finding local or global minima. Since the tool is based on a technical database of existing PV and battery systems dimensioning steps correspond to the related module sizes.For such a discrete problem, only optimization algorithms with a non-derivative method can be used [3]. Additionally, the problem is non-linear which further reduces the number of suitable algorithms.

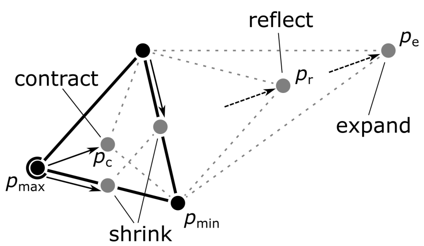

Fig. 1. The different operations of the Nelder-Mead algorithm graphically explained [5]

A. Single-Objective Optimization

For identifying the best possible values for levelized cost of energy and CO_2-savings, optimization is done initially for both objectives solitary without evaluating other objectives during the optimization process. For this purpose, two algorithms were compared which are able to minimize non-linear integral problems. On the one hand, there is the downhill simplex method after NELDER-MEAD. Other than the more common Dantzig's simplex algorithm, it is able to solve non-linear problems.

A simplex is a n-dimensional body with n+1 corners, while n being the number of parameters of the objective function. The coordinates of the corners are described by the function parameters. In this case, there are two parameters, installed PV power and battery capacity, thus, the simplex is a triangle. In every iteration the function values at the corners are evaluated and compared. The simplex changes its shape and position via expansion, contraction, reflexion or shrinking by changing the position of the corner bearing the worst function value respectively moving the worst and the second worst point towards the best one in case of shrinking. These procedures are described in Fig. **??**. During several iterations the simplex becomes smaller and moves towards lower function values. The choice of an adequate initial point is crucial, otherwise, the solver will halt at an unfeasible local minima [4].

The genetic algorithm mimics evolutionary processes to find local and global minima. A certain quantity of instances is created, each one is assigned a random set of parameters. In each iteration, for every instance the function values is evaluated. Instances with the most adequate function values are moved to the next iteration without changes, while instances with the worst function values are removed from the pool. The other ones are either randomly mutated or mixed to create new instances. [6], [7]

For comparing these algorithms in MATLAB the functions ga for genetic and fminsearch for simplex optimization are used. Additionally, fminsearch was expanded by additional functions to account for constraints like minimum and maximum number of batteries and PV modules.[8]

B. Multi-Objective Optimization

When optimizing several competing objective functions at once, not only points minimizing one particular function are of interest, but also solutions in between. The goal is to find the most suitable trade-off between the different objectives. The basic criterion for a solution is to be pareto-optimal, meaning that one objective value can only be improved at the cost of degrading another one. For instance, at a pareto-optimal point, the CO_2 emissions can only be reduced further by adding PV and/or battery systems, thus increasing the investment costs. There is no other configuration for the same or a lower price that leads to less emissions. Deciding which pareto-optimal solution is the most desirable, requires additional information. How this information is applied varies between different methods for solving multi-objective problems. For the PV-Diesel system, methods of scalarizing were used. The problem is reduced to a single objective-problem during the optimization process. This was done both by using either a weighting function or the ϵ-constraint method, respectively.

For the weighting function, each objective function f, a certain weight w is assigned. The sum of the weighted objectives is then minimized.

$$min \sum_{i=1}^{n} f_i(x) \cdot w_i \tag{1}$$

On the other side, for the ϵ-constraint method just one of the results is regarded as an actual objective, the other ones are used as additional constraints.[9]

$$\begin{gathered} min\ f_l(x) \\ f_j(x) \leq \epsilon_j,\ j = 1...k,\ j \neq l \end{gathered} \tag{2}$$

For instance, the solver will try to minimize the investment cost while archiving a certain saving of CO2-emissions. Both algorithm are compared in Fig. 2 Besides that defin-

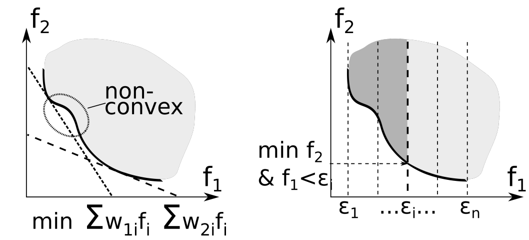

Fig. 2. The method of weighting function (l) to the ϵ-constraint method (r) is compared. Former is not able to find all pareto-optimal solution on non-convex functions

ing appropriate weights might be difficult, the weighted method is not able to identify all pareto-optimal solutions on non-convex functions. Further on, accurate constraint values rather than weights are better understandable for the user. Therefore, the ϵ-constraint function was preferred.

C. Application

To identify different points on the pareto-front, optimization is done for several ϵ values. These are evenly distributed between the respective optima. The number of ϵ values created can be chosen by the user. The more values are identified, the higher the resolution of the pareto front and calculation time. For this paper, four additional ϵ constraints were used for a higher resolution at critical areas, resulting into a total of fifteen points including optima of the solitary objective functions. The constraint is implemented by extending the objective function by a

sub-function. Is a constraint exceeded, the sub-function applies a penalty to the function value which is returned to the optimization algorithm.
To reduce calculation time and because LCOE can be understood as a function of investment and fuel costs, hence CO_2-savings, only investment cost and CO_2-emissions as competing functions are used for the ϵ-constraint method. LCOE can later be calculated using the solutions identified by the two-objective optimization. Thus, changing fuel prices does not require a new optimization run.

IV. RESULTS

A. Comparison of simplex and genetic algorithm

In the beginning, simplex and genetic algorithm were compared to each other using a set of random starting points and boundary conditions. The simplex algorithm converged smoothly and fast in under 20 iterations if given a starting point within plausible limits. As plausible limits the quadruple values of the point with lowest LCOE found in a manual search, were chosen arbitrarily. Specifically, the bounds were 240kW PV and 250kWh of battery. Assigning randomized, yet higher starting points lead to a significant higher calculation time, as shown for two starting points in Fig. 3. For finding reliably global minima,

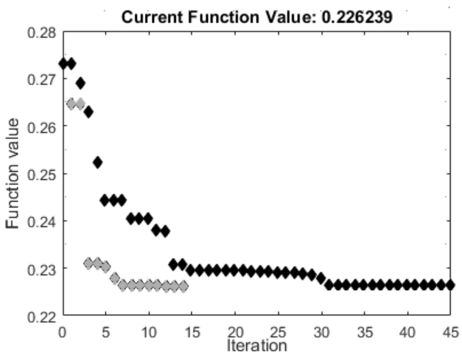

Fig. 3. Convergence with simplex algorithm for plausible (l) and implausible (r) upper bounds

it was found that the genetic algorithm needs at least 10 instances. This means, that after two iterations the genetic algorithm already counts more function evaluations than the simplex algorithm. Until convergence, the genetic algorithm ran at least 10 iterations or up to 25 when using higher upper bounds, resulting in more than 100 function evaluations, as shown in Fig. 4. So while the number of iterations needed by the Algorithm Genetic Algorithm might even be lower as for the simplex one, the number of function evaluations and thus calculation time is much higher, as a single function evaluation requires a whole simulation run. However, the calculation time also strongly depends on the distance of the starting point to the optimum.
The superior convergence of the simplex algorithm is due to the smooth course of function with only a small number of local minima. Otherwise the algorithm might not find the desired minimum at all.

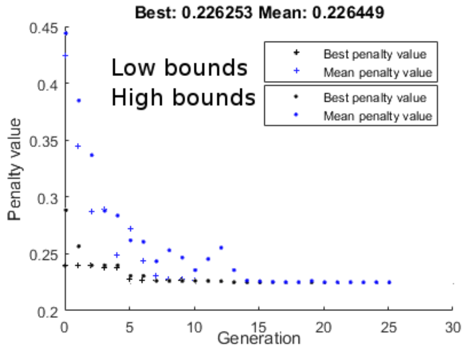

Fig. 4. Convergence with genetic algorithm for plausible (l) and implausible (r) upper bounds

B. Single-Objective Optima

The most interesting objective for a single-objective optima is LCOE, since it lies within the room of feasible solutions rather than at the boundaries. It is archived when both CO_2-emissions and investment costs are relatively low. The position of the optimum varies with changed market prices. For the given system, the optimum was with 56kW of PV and 71kWh of batteries.
The optimum of investment cost is obviously the reference case, no PV and battery systems are installed at all. In this case, only the new set of generators has to be paid for. The optimum for CO_2-Savings is 100%. This value is reached when both PV and battery systems exceed a certain threshold. There are endless points reaching this optimum, however, only the one solution including both threshold values offers a minimum of investment cost, which opens the field for multi-objective optimization.

C. Multi-Objective Optima

As stated in part III-C, multi-objective optimization was done for investment costs and CO_2-savings. Investment costs were used as primary objective while using different CO_2-savings as ϵ-constrain. It should be noted that the solving time of a single ϵ-constraint optimum rises considerably compared to the optimization without an ϵ constraint, a majority of the iterations is spent evaluating points near the final optima but exceeding the limiter.
The results are given in Fig. 5. Each point represents the cheapest possible option to achieve a certain reduction of CO_2-emissions. It can be seen that investment costs rise continuously for a higher reduction of emissions, because a bigger PV and battery system is required. Even values of 98% can be reached within reasonable boundaries. For a very high reduction of emissions, much bigger investments are needed. This is quiet consistent with other literature, which indicate the need of unfeasible big battery and PV systems for high autarky degrees. [10]
Diesel prices vary drastically for different places in the world. From the identified pareto-optimal points in Fig. 5, LCOE can quickly be evaluated using different prices. In Fig. 6, LCOE are given for low diesel prices in Egypt of 0.2$/l and medium ones in Tunisia of 0.65$/l, as well as the high reference price of 0.9$/l which was the global average at the time of last check-up[11].

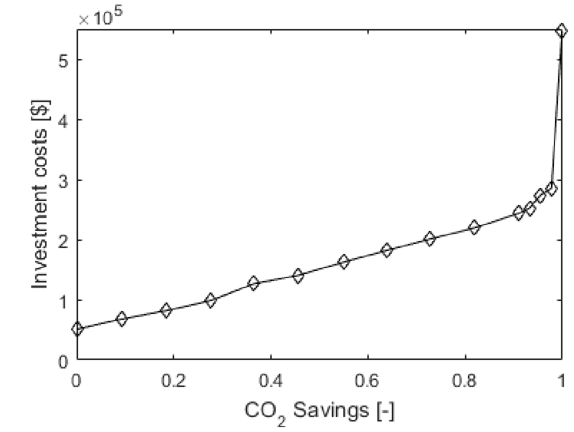

Fig. 5. Pareto-Front of optimization of CO_2-savings and investment costs

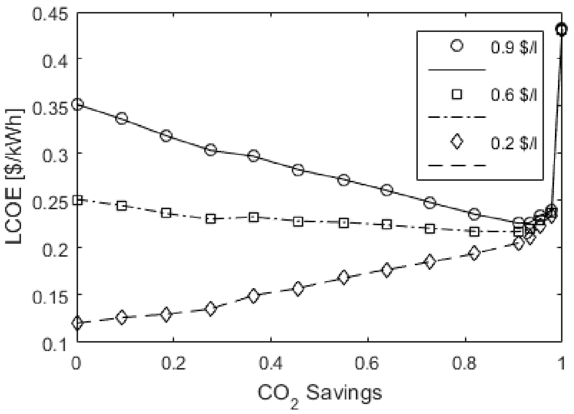

Fig. 6. LCOE over CO_2-Savings for different prices of diesel on CO2 vs. investment costs - optimal points

It should be noted that investment cost and not LCOE are optimal for the given points. In case of the reference, or even higher prices, as found in India, China and most western countries, LCOE falls with a higher reduction of emissions, which is due to the lower spending on expensive fuel. For very low fuel prices, LCOE actually rises which higher reduction, as fuel costs are almost negligible and investment costs are dominant. In between LCOE remains constant for medium prices. For higher reduction of emissions, different LCOE come closer to each other as investment costs become more dominant even with high fuel prices. For a very high reduction, spending on fuel is negligible while as investment costs become very big, hence no difference between fuel prices is recognizable.

According to Figure 7, the pareto optimal sizes varies up to a 151 kWp PV system and 157 kWh battery capacity. However, CO_2 savings of 98% are already achieved at 66 kWp and 90 kWh. In case of a diesel price of 0,9 $/l, the minimum LCOE is achieved with 56 kWp and 69 kWh. Furthermore, batteries larger than 3 kWh are only pareto optimal with PV plants larger than 26 kWp.

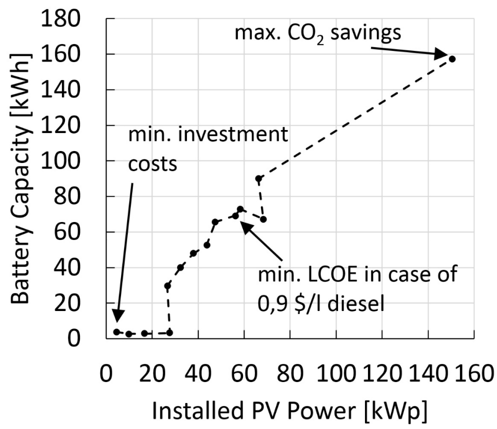

Fig. 7. Battery capacity and installed PV power according to the pareto front between the optima of CO_2 savings and investment costs.

V. Conclusion

In this paper, different optimization algorithms were used on a simulating tool for PV-Diesel-hybrid systems. It was found, that a downhill-simplex algorithm converges in under a fifth of the time the genetic algorithm needs, due to the shorter calculation time per iteration.

The optimal dimensioning of PV-modules and battery storage for low LCOE can quickly be identified, often in under 25 iterations. For a compromise between low CO_2-emissions and investment costs it is now possible to visualize and compare an arbitrary number of pareto-optimal points using the ϵ-constraint method. It was found that there is one dimensioning of PV and battery systems for an optimal LCOE and investment cost rise with CO_2-savings roughly linearly up to 98% of saved emissions. However, costs rise sharply beyond this point.

The created tools can be used in development projects where a PV-diesel hybrid system might be installed. The size of the PV and battery systems for the most economical and/or ecological supply of energy is efficiently determined.

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