Optimization of retail electricity pricing structures

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Summary

The effect of variable electricity pricing can be evaluated by simulation. Consumers and their potential demand-side management measures are modelled based on their individual load curves in order to examine different pricing structures. The optimal rate coefficients can be determined by nonlinear optimization. This paper compares different optimization algorithms for this task depending on the complexity of the respective rate and subsequently deduces a recommendation for further evaluations.

1 Introduction

The transition towards an energy system with a high share of renewables creates new requirements for flexibility in the system. Residential consumers can contribute by adjusting their consumption behavior if they are incentivized properly [1]. This can be achieved by several variable pricing structures, which appear to have varying effectiveness [2, 3].

Simulations of the customers' reaction to price signals can help to evaluate the effects of different rate structures. Previous investigations show that conventional time-of-use pricing cannot be recommended [4]; therefore, a more dynamic approach is considered here. Since this involves a lot of variable coefficients, an optimization strategy for finding the best solution is developed.

2 Methods

2.1 Rate structure

The effects of time-of-use rates with two different price levels (illustrated in figure 1) on several relevant objectives were evaluated in previous work [4]. These rates are characterized by two coefficients that describe the daily time window with high prices. These apply to all days of the year and are optimized regarding energy purchase costs.

The investigations led to two main conclusions:

- Time-of-use rates with the described structure do not yield satisfactory results.
- The approach of simulating all possible combinations of rate coefficients is computationally very intensive.

Therefore, more complex rates are to be investigated for application in the household sector. Since the computation time for the variation of two coefficients in hourly resolution is already quite high, the previous approach is not feasible. For the assessment of alternative algorithms which determine the optimal coefficient set, two additional rate structures are considered. These depend on three or four coefficients, respectively, and therefore, allow evaluating the performance of these algorithms:

The first one is based on the simple time-of-use rate and introduces an additional coefficient, which is used as a threshold to identify critical prices. This means that the high price level is applied for the hour with highest energy purchase costs, if these costs exceed the defined threshold value. For days that never exceed this value, the aforementioned structure with two intervals is applied. This can be considered a possible implementation of the so-called critical peak pricing [5].

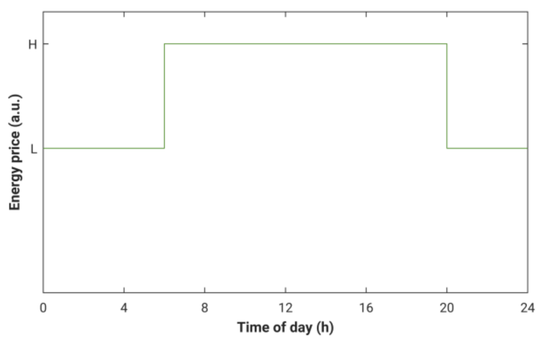

Figure 1 Time-of-use rate with two price levels

The second new rate structure under investigation extends this model to another coefficient which defines the duration of the interval. By contrast to the one before, the critical-peak pricing is not only applied to the hour with highest purchase costs, but also to a variable time window around it.

To summarize, three different rate structures are considered, with two, three or four variable coefficients, respectively. All coefficients are treated as continuous values, so no hourly grid is applied here. The specific rate implementations are not meant as prototypes or recommendations for useful rate structures, but serve as examples in order to evaluate different algorithms regarding their applicability for different numbers of coefficients.

2.2 Simulation of consumer reaction

Residential consumers are characterized by measured individual load curves in the simulation. In order to quantify their reactions to given price signals, appliances which are considered suitable for demand-side management measures are identified in these load curves via a pattern recognition algorithm [6], and subsequently shifted to the economically optimal time of operation within an acceptable interval [4]. This process is depicted in figure 2.

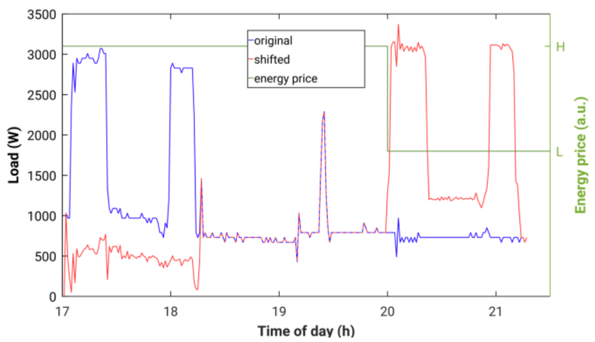

Figure 2 Load shifting of individual appliances

Since the actual customer behavior is currently being investigated via surveys, a simplified model is applied here. This does not include individual price thresholds for DSM measures, nor does it consider individually accepted delay intervals. Therefore, the results given below are not to be considered final regarding the actual effectiveness of the rate structures, but serve for evaluation of the optimization algorithms.

2.3 Optimization algorithms

The rate coefficients are determined with three different algorithms for nonlinear optimization of non-differentiable and non-continuous objective functions:

- Pattern search
- Simulated annealing
- Genetic optimization

For all these algorithms, the standard MATLAB implementation is used [7]. Besides the optimization goals described in the next section, no additional bounds or constraints are applied.

Pattern search works by iteratively approaching the optimal point by computing the surrounding mesh points of the current solution and iteratively refining the mesh size [8]. In contrast to the following algorithms, this one is deterministic and therefore, yields the exact same results if applied repeatedly. The chosen parameters are given in table 1.

Simulated annealing is a heuristic method for global optimization. It is based on randomly generating points with decreasing distance from the current point and models the physical process of minimizing system energy by lowering temperature [9, 10]. Table 2 shows the applied parameter set.

Parameter	Value
Poll method	GPS Positive basis 2N
Polling order	Consecutive
Initial mesh size	1
Expansion factor	2
Contraction factor	0.5

Table 1 Parameters for pattern search

Parameter	Value
Annealing function	Fast annealing
Reannealing interval	100
Temperature update function	Exponential
Initial temperature	100

Table 2 Parameters for simulated annealing

Genetic optimization models the evolutionary process of natural selection. It works on a set of individual solutions, which are repeatedly modified by random changes and/or by combination of existing solutions [11]. The parameters are listed in table 3.

Parameter	Value
Population size	50
Elite count	2
Crossover fraction	0.8

Table 3 Parameters for genetic optimization

These algorithms are applied to the described optimization problem and evaluated regarding their performance, as explained in the next section.

2.4 Assessment methodology

Variable electricity rates can be designed for different purposes like reduction of purchase prices, reduction of greenhouse gas emissions or reduction of grid load [4, 12]. Since the goal of this paper is to assess the optimization methods, only one objective is considered here: the reduction of the average energy purchase costs for all considered residential consumers, evaluated regarding the spot market prices at EPEX spot [13].

Since the simulation of customer behavior to a given set of coefficients, thus the evaluation of the objective function, is the most time-consuming part of the computation, this is the relevant criterion for comparison of the algorithms. Therefore, the optimization algorithm with least function evaluations for a sufficiently precise solution is preferred.

Also due to the computational effort, the objective function is only evaluated at discrete points and interpolated in between. This does not yield perfectly correct results regarding the resulting purchase costs, but

allows assessment of the optimization algorithms for continuous coefficients in reasonable time.
All considered algorithms depend heavily on the choice of a starting point; simulated annealing and genetic optimization also inherently depend on generated pseudo-random numbers within the optimization process. To account for these influences, every optimization problem is solved repeatedly 100 times with randomly chosen starting points and evaluated regarding the success rate, which means the number of configurations that lead to a sufficiently precise solution. The solution is considered sufficiently precise when the resulting minimum deviates by at most 0.01 % from the actual minimum.

3 Results and Discussion

3.1 Two rate coefficients

Table 4 shows the success rates for the considered algorithms. The success rate describes the ratio of optimization runs that lead to the optimal solution and therefore, a high rate is desirable.

Algorithm	Success rate
Pattern search	97 %
Simulated annealing	98 %
Genetic optimization	98 %

Table 4 Success rates (two coefficients)

All evaluated algorithms evince quite good results, since the values are above 95 %. This means that more than 95% of the randomly chosen initial configurations lead to a result which is considered sufficiently precise. Therefore, for rate optimization problems with two coefficients, the choice of the optimization method is not critical, as long as runtime is not an issue.
The detailed results for pattern search in figure 3 show that some outliers deviate by more than 1 %. This indicates a local minimum of the objective function, which prevents the solver from approaching the global minimum. For comparison: the deviation of the starting value is 2.1 % in the worst case.

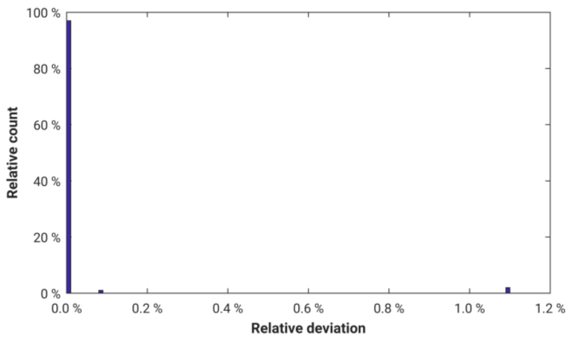

Figure 3 Pattern search results (two coefficients)

Although there are also some values that do not fulfil the precision requirements for the other algorithms (cf. figure 4 and figure 5), these show comparatively small deviations. Thus, the probabilistic methods seem to be more suitable for rate structures that cause significant local minima in the objective function.

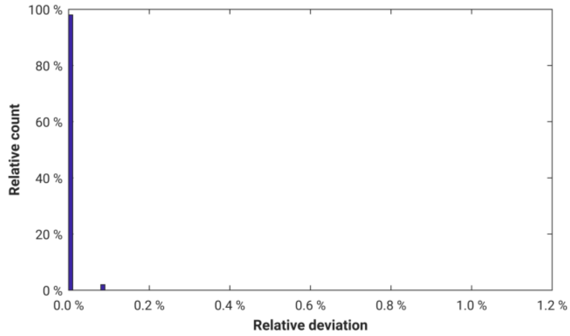

Figure 4 Simulated annealing results (two coefficients)

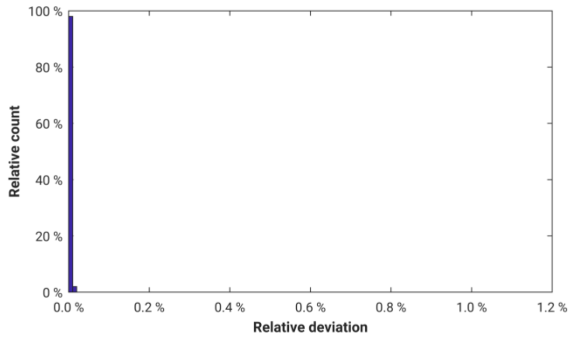

Figure 5 Genetic optimization results (two coefficients)

But as explained before, the expected runtime, measured by the number of function evaluations, is also an important assessment criterion. The mean numbers of function evaluations for all optimization runs that lead to sufficiently precise results (as defined above) are listed in table 5.

Algorithm	Function evaluations
Pattern search	28
Simulated annealing	154
Genetic optimization	214

Table 5 Mean function evaluations (two coefficients)

The numbers show that pattern search requires significantly less evaluations of the objective function, and thus, the expected runtime is much lower. For rate structures with few degrees of freedom, this suggests the preferred application of pattern search algorithms. This observation is also confirmed by the distribution of function evaluations depicted in figure 6. It is presented as a boxplot with the following elements: The red bar and the red plus indicate median and mean value, respectively; the quartiles are given by the blue box and the total range of values by the black whiskers.

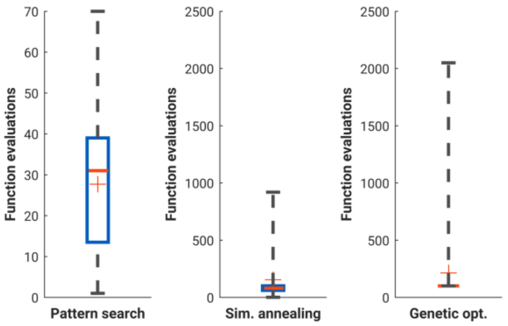

Figure 6 Function evaluations (two coefficients)

The graphs show that even in the worst case, pattern search requires less function evaluations than the other algorithms in the average case, therefore, probabilistic algorithms are not recommended for this kind of problem.

3.2 Three rate coefficients

Analogously to the previous section, table 6 shows the success rates of the described algorithms for the rate structure with three coefficients. As before, a high rate describes a high probability of solving the optimization problem from a randomly chosen starting point.

Algorithm	Success rate
Pattern search	91 %
Simulated annealing	50 %
Genetic optimization	94 %

Table 6 Success rate (three coefficients)

Pattern search and genetic optimization perform comparably well as before with a success rate of more than 90 %, whereas simulated annealing provides useful results in only 50 % of the examined cases. Therefore, this method seems to be unsuitable for the problem structure under investigation.
The detailed analysis of pattern search results in figure 7 shows similar behavior as for the rate structure with two coefficients, since a small number of outliers suggests local minima that complicate the solving process.
As the low success rates already shows, the results for simulated annealing are not satisfactory with respect to the defined precision. However, the detailed results in figure 8 evince an accumulation at comparatively low deviations, which means that the performance of the method could be considered quite well in case of higher thresholds and therefore, lower accuracy requirements.
Nevertheless, outliers in a similar range as for the pattern search algorithm exist, which also indicates the aforementioned presence of local minima in the objective function.

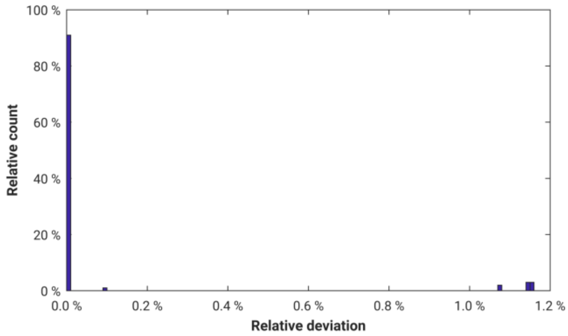

Figure 7 Pattern search results (three coefficients)

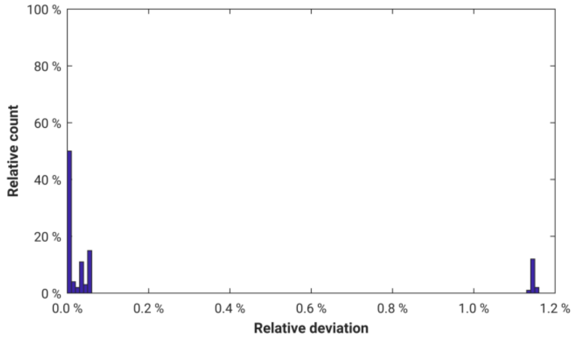

Figure 8 Simulated annealing results (three coefficients)

However, this can be overcome by genetic optimization, as the results in figure 9 show. Therefore, this method is the best choice regarding precision in this case.

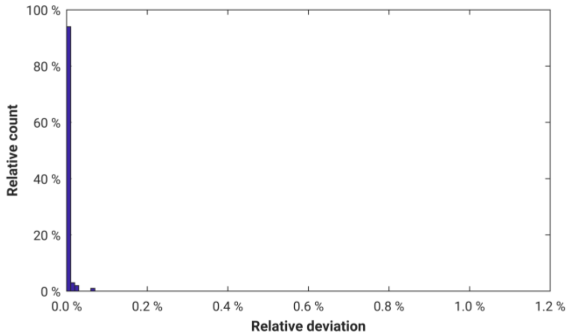

Figure 9 Genetic optimization results (three coefficients)

The second important criterion is again the number of function evaluations, since this number is decisive for the runtime of the whole optimization process. The mean values for the successful configurations are displayed in table 7.

Algorithm	Function evaluations
Pattern search	69
Simulated annealing	746
Genetic optimization	1382

Table 7 Mean function evaluations (three coefficients)

As expected, pattern search requires the least number of function evaluations compared to the probabilistic methods. This is also confirmed by the distributions depicted in figure 10, which again show that pattern search in the worst case is still significantly less expensive than the other algorithms in the average case.

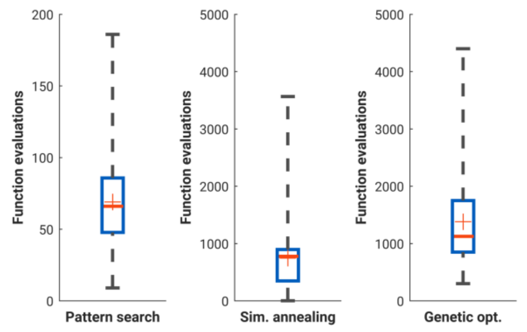

Figure 10 Function evaluations (three coefficients)

Due to the low success rate, simulated annealing cannot be recommended here. Depending on the importance of low runtime of the optimization process, either pattern search or genetic optimization are to be applied.

3.3 Four rate coefficients

For the extended optimization problem with four coefficients, success rates drop significantly. However, genetic optimization still shows the best performance with respect to the defined thresholds. The values for all considered methods are shown in table 8.

Algorithm	Success rate
Pattern search	70 %
Simulated annealing	50 %
Genetic optimization	80 %

Table 8 Success rates (four coefficients)

The comparison of the detailed results in figure 11, figure 12 and figure 13 shows that all three methods have problems with local minima in the same deviation range.

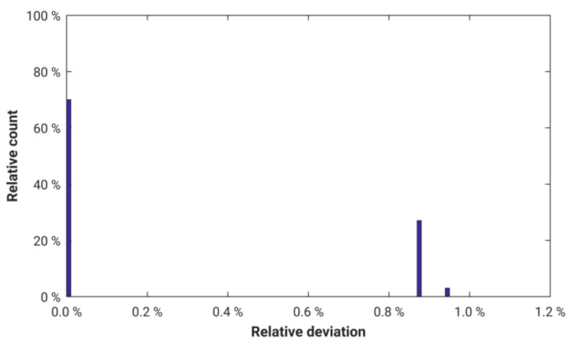

Figure 11 Pattern search results (four coefficients)

As already deduced in the previous section, genetic optimization handles these in the best way and therefore yields the best results with respect to success rates.

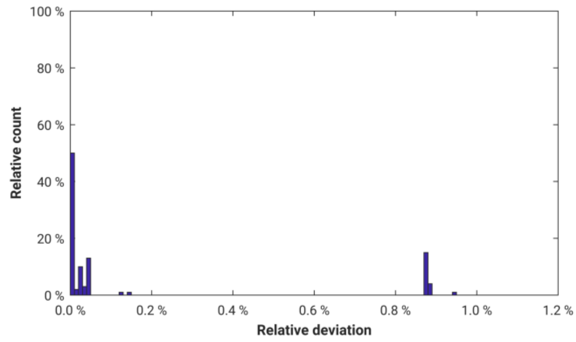

Figure 12 Simulated annealing results (four coefficients)

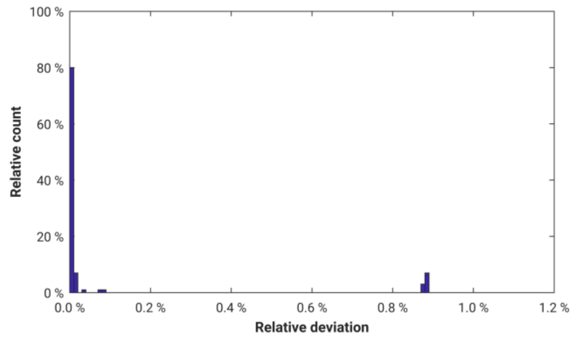

Figure 13 Genetic optimization results (four coefficients)

The number of function evaluations in table 9 shows the same structure as for two and three coefficients: pattern search is the least expensive algorithm, whereas the computational effort for simulated annealing and genetic optimization is considerably higher.

Algorithm	Function evaluations
Pattern search	94
Simulated annealing	814
Genetic optimization	1795

Table 9 Mean function evaluations (four coefficients)

The boxplots depicted in figure 14 again lead to the conclusion that in the general case, probabilistic methods cause significantly higher computation time. The worst-case estimation shows that the number of function evaluations is higher by a factor of more than 25.
To sum up, the best results for rates structures with four coefficients are achieved with genetic optimization. However, the computational intensity and complexity is by far higher, therefore, the practical applicability of pattern search is higher, with still comparably good results.

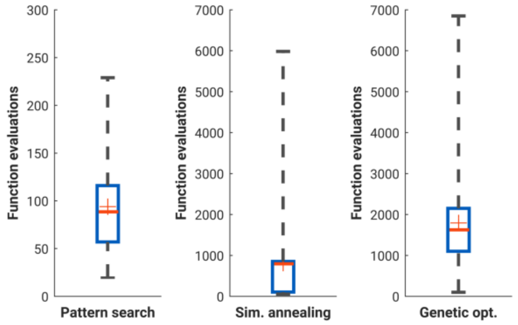

Figure 14 Function evaluations (four coefficients)

4 Conclusion and Outlook

The computations and comparisons show that for a simple optimization of two rate coefficients, the choice of the right algorithm is rather insignificant. For more complex rate structures, the performance of simulated annealing regarding the precision of the solution is unsatisfactory. Thus, it cannot be recommended to apply this kind of algorithm to the optimization of rate coefficients.
Genetic optimization yields the best results regarding accuracy, but is computationally very intensive, since it requires a significantly higher number of function evaluations than pattern search. For application to a large data set, this might render impractical, leaving pattern search as a general recommendation in this case. For smaller data sets or for purposes where computation time is not significant, genetic optimization can be applied according to the simulation results.
Several future improvements are possible and also necessary for more complex rate structures with more degrees of freedom. To speed up the whole computation process, the optimization problem can be reduced from continuous variables to discrete ones. Since coefficients of electricity rates in general represent some kind of threshold value in terms of e. g. price, load or generation, or some time of the day or week or year, discrete values are actually what consumers expect, and therefore, are sufficient to describe the rates. With the right choice and implementation of the optimization algorithm, this might significantly reduce the search space.
As the distributions of the optimization results show, the choice of starting values is critical for both accuracy and computational effort. Thus, smart heuristics that determine these values based on both previous results and on requirements deduced from the energy system can help to improve both indicators.
Literature suggests the application of particle swarm algorithms to similar optimization problems [14]. This is not included here, but will be also checked in future investigations and can potentially serve as a suitable optimization method. Another possibility might be the combination of the described algorithms in order to use advantages and avoid the respective disadvantages, e. g. by generating starting values for genetic optimization via pattern search.
With all these improvements implemented, the parameters of the resulting best method are to be adapted to the specific application. This is expected to further reduce computational effort, thus, to satisfactory results in lower runtime.

5 References

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