Evaluation of the effects of time-of-use pricing for private households based on measured load data

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***Abstract*—Based on measured load data in high temporal resolution, the time-dependent load shifting potential of residential electricity customers can be assessed. This enables the simulation of their reaction to different variable retail electricity rates, and consequently the evaluation of the suitability of these rate structures for various applications. The focus is on time-of-use rates with two price levels, which incentivize load shifting from high to low prices. The results show that this kind of rate structure is not the optimal choice for the examined applications; therefore, it is recommended to include additional rate elements like demand charges or peak pricing. However, the high computational effort suggests the development of a new rate optimization strategy for the introduction of additional parameters.**

***Index Terms*— demand-side management, electricity pricing, time-of-use pricing**

I. INTRODUCTION

Many of current and future challenges for the energy system, such as reduction of greenhouse gas emissions or integration of volatile renewable energy sources, can be tackled by additional flexibility in the system. In addition to flexible power generation, flexible consumption is an integral part of these flexibility requirements. In order to tap the potential, incentive systems for different consumer groups have to be developed and established. One of these consumer groups are private households. These account for roughly one fourth of Germany's total electric energy consumption and can consequently contribute substantially. For the identification of suitable rate structures and rate systems, measured load data of real households can be used. This allows for simulating the effect of different rates on individual customers and for determining their suitability for given purposes.

II. METHODS

A. Load data and usage patterns

The simulations are based on measured load data for over two thousand households. These have been recorded by a German municipal utility using smart meters and are available in a temporal resolution of one minute for a full year (August 2014 to July 2015). After excluding data sets with poor quality and interpolation of minor gaps, 565 sufficiently complete load curves are available for further analyses [1]. Fig. 1 shows the normalized mean daily profile of these households, compared to the weighted mean standard load profile for Germany. Although there are some marginal differences, the overall shape, i. e., the distribution of peaks and dips is quite similar. Therefore, the following investigations can be considered sufficiently representative for German residential customers.

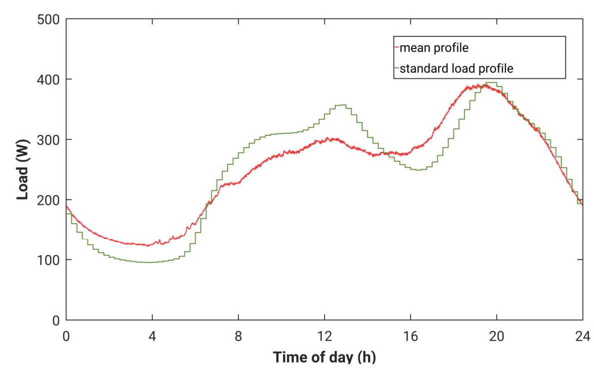

Figure 1. Mean daily load profile

For the simulation of demand side management (DSM) measures induced by price spreads, relevant appliances are identified in the load data for each household. The selection criteria in this context are high energy consumption and assumed acceptance for DSM measures, which leaves dishwashers, washing machines and dryers as suitable appliance types [2]. A data mining algorithm based on hierarchical clustering of extracted load patterns and identification of appliance types by characteristic features is used for disaggregation of the total load curve and provides operation time and load profiles of all identified appliances with potentially flexible operation [1].

B. Rate structures

A wide variety of variable rate structures for residential electricity customers has been applied in different regions and

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discussed in several research projects [3]–[6]. All of them are designed in order to incentivize desired customer behavior with suitable pricing elements, e. g. time dependency, load dependency, real time pricing, peak pricing or demand charges.

To reduce these infinite possible rate structures, only time-of-use rates with two price levels defined in hourly steps are considered here. The structure is schematically depicted in fig. 2. It includes some hours with high energy price (*H*, in the example 6 am to 8 pm) and another interval with low energy price (*L*, the remaining time of the day). Therefore, customers can reduce their electricity costs by partially shifting their energy consumption from *H* to *L*.

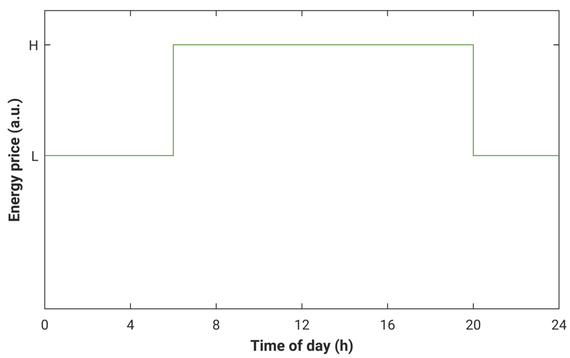

Figure 2. Example of time-of-use rate structure

The described rate structure can be implemented with conventional double-rate meters and does not require smart metering systems. Moreover, this simple structure is quite convenient for customers to adapt to, compared to more dynamic pricing approaches like critical peak pricing or demand charges. Therefore, it is examined which goals can already be reached with this kind of rates, and which ones require more sophisticated structures.

Considering interval boundaries only at full hours, a total number of $24 \times 23 = 552$ rates according to this structure, i. e., with one closed *H* interval, are possible. These will be evaluated in the following simulations.

C. Applications

Variable electricity pricing can be used for various purposes and applications, which have different requirements regarding DSM measures. The described time-of-use rate variants are investigated with regard to the effect on the following applications:

1) Energy purchase costs

The prices for electric energy on the wholesale market are strongly time-dependent. Fig. 3 shows the mean daily profile of EPEX day-ahead prices in the considered year [7]. Shifting consumption from price peaks like noon or early evening to low price regions at night enables monetary savings potential for the utility, which can be quantified with the simulation.

For the evaluation, it is assumed that (compared to the whole market area) only a small number of customers adopts the new rates and changes their behavior, so that feedback effects [8] on wholesale prices can be neglected.

2) Greenhouse gas emissions

Due to fluctuating renewables and varying operation of conventional power plant types, greenhouse gas emissions (GHG) induced by electricity generation are also time-dependent [9]. Therefore, residential DSM can contribute to a reduction of GHG emissions and consequently to environmental goals. Again, feedback on hourly emission coefficients due to a change in the generation mix is not considered, so the results are only valid for a small number of customers and on a short-term perspective.

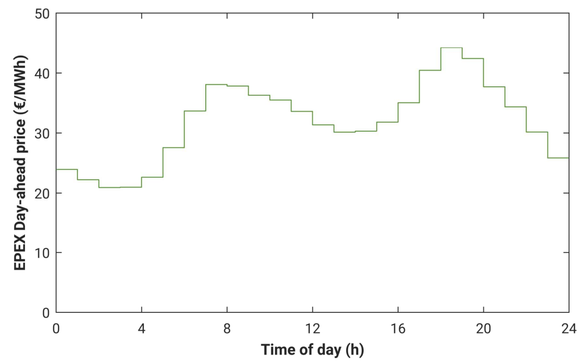

Figure 3. Mean daily EPEX day-ahead prices

3) Peak load

Components of an electricity grid, like power lines and transformer stations, have a maximum capacity that cannot be exceeded, because this would cause failure of the system. This means that the peak load in a year should not reach or exceed a specific threshold below this maximum value, since otherwise grid reinforcement and expansion would be necessary. Time-of-use rates can also help to reduce these high load peaks by shifting appliance use to off-peak hours.

4) Photovoltaics peak

Another common problem on low voltage grid level is high photovoltaics (PV) generation, leading to negative load at the transformer station in peak hours and thus undesired effects on higher grid levels. Depending on the market setting, there might be an incentive for customers to increase self-consumption by DSM or other measures already in place [10], [11], but this is not the case for greenfield PV plants. However, rates which induce load shifting to hours with high PV generation can lead to a reduction of this problem. Here, a PV plant with a peak power of 300 kW is simulated [12], matching the total peak load of all customers.

5) Multiple applications

Dealing with competing goals which should be reached at the same time is another important issue that has to be addressed. The selection of an optimal rate or an optimal set of rates for a given application might affect the other applications negatively; e. g., optimization of purchase prices might increase GHG emissions or load peaks. These interdependences are evaluated for all combinations in order to identify positive and negative synergies.

D. *Simulation*

The computation of the rates' effects on the described criteria consists of two main parts: simulation of customer behavior and resulting load curves, and afterwards evaluation of the defined target values:

1) *Customer behavior*

For the simulation of the customer reaction to given rates, it is assumed that the price spread between the two levels is large enough to motivate the customer to delay their usage of relevant appliances according to the price. This assumption yields an upper estimate of the DSM potential and is applied in order to quantify the general suitability of time-of-use rates.

The simulation optimizes the operation time of recognized appliances within a certain interval (8 hours) after the original operation time in order to achieve lowest operation cost [10]. This process is illustrated in fig. 4 and yields a new load curve per household and rate, which is evaluated in the following step.

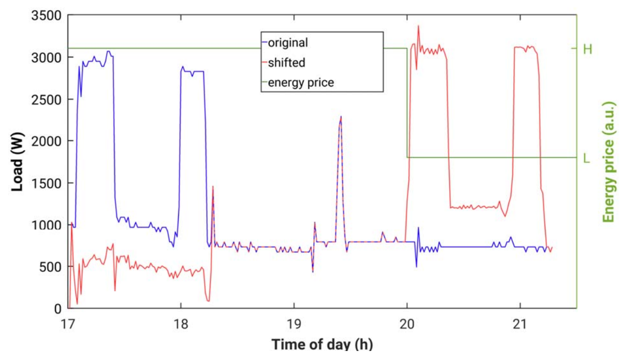

Figure 4. Load shifting of individual appliances

2) *Evaluation*

The suitability of time-of-use rates with two price levels for the aforementioned applications is determined by choosing the rate with the best result for the respective target value. Also the distribution of results for all simulated rates is evaluated in order to assess the stability of the results.

III. Results and Discussion

A. *Validation*

The described simulations yield a large number of load curves for the considered rates. Therefore, thorough validation of the employed algorithm by analyzing single data sets is impractical. In order to nevertheless ensure correct simulation results, two validation steps are used.

A simple possibility to check the applied load-shifting algorithm is the calculation of the total consumption per customer. Delaying the operation of household appliances should not alter this value, since it removes the same amount of energy from the original point in time which is added at the optimal point within the optimization interval. The differences between the original consumption and the resulting values after performing the simulated DSM measures are in the order of 10^{-12}, which can be explained by numerical effects of the computations and therefore support the correctness of the implemented approach.

Moreover, the optimization algorithm of the operation time can be validated by comparing the original consumption during *H* intervals with the consumption of the shifted load curves in these intervals. This shows that mean consumption in the respective intervals decreases as expected, therefore the shifting procedure from *H* to *L* intervals works as designed.

B. *Computational effort*

According to the described methodology, new load curves with shifted appliances have to be calculated for all customers (565) and all considered rates (552). Due to the large data base and the high average number of recognized appliances per customer (225), these computations take several days on recent hardware. This shows that the current approach is only applicable for a reduced set of rates like the one investigated here, but not for a comprehensive comparison and optimization of variable rate structures.

Memory requirements pose another limitation. The resulting load curves with temporal resolution of 1 minute account for about 1.2 TiB, which also confirms that the approach of simulating every possible rate of the considered structure will render impractical for further investigations. Therefore, an optimization method for identification of the ideal rate which does not require all options to be simulated is necessary.

C. *Applications*

The effect of time-of-use rates on the relevant applications described in II: C. is quantified according the evaluation procedures given in II. D. and presented in the following sections:

1) *Energy purchase costs*

Fig. 5a shows the distribution of energy costs for the simulated rates, averaged over all customers. 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. For comparison, the values are normalized to the energy costs of the original unaltered load curves. For the ideal rate, a reduction of 1.29% is possible, but there is also a large set of rates which has negative effects.

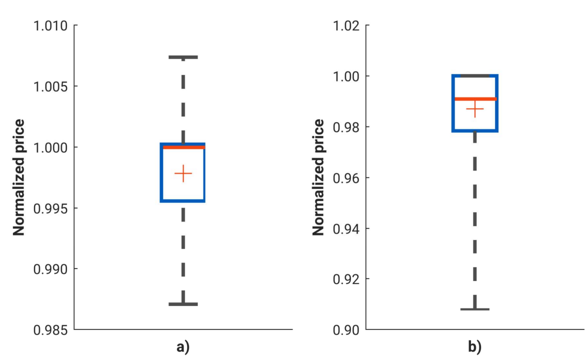

Figure 5. Reduction of energy purchase costs for best rate

Detailed investigation of the chosen ideal rate per individual customer yields the distribution depicted in fig. 5b. Despite the average reduction of purchase costs, there are a lot of customers with very small improvement. The reason might be the lack of an overall optimal rate, which thus has to be tailored to each customer group for best results.

Therefore, figure 6a shows an analogous analysis, where the optimal rate per customer is applied. As expected, a reduction of purchase prices for all customers occurs again. On average, a reduction of 1.36 % can be reached, but this would require the application of 28 different rates for the examined 565 customers. Thus, this has to be considered an idealized case and is not reasonably replicable in practical application.

It is assumed that a set of three different rates is feasible without undue effort. With reduction to the three best rates for the individual customers, the reduction shrinks to 1.33 %, but is still superior compared to only one rate. The resulting distribution is displayed in fig. 6b. The overall differences between the three versions are very small, thus this variant might be the best recommendation.

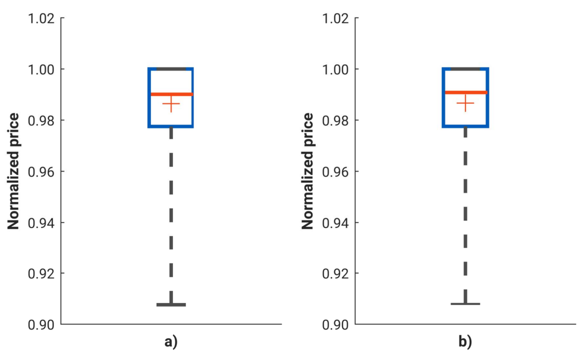

Figure 6. Reduction of energy purchase costs for individual rates

Fig. 7 compares the resulting mean daily load profile for the selected three rates with the original one. It shows a shift of energy consumption from evening hours to the early morning between 0 and 4 am. The peaks stem from the hourly rate structure, which results in shifting to full hours.

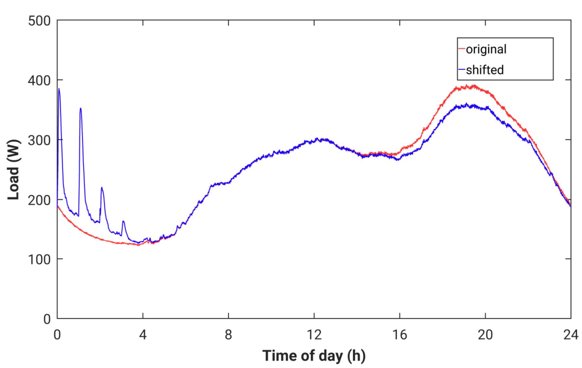

Figure 7. Resulting mean daily load profile for 3 rates

2) Greenhouse gas emissions

For the reduction of GHG emissions, the results are presented analogously to the previous section about energy purchase costs. The graphs for the best rate are shown in fig. 8. With optimal choice of one rate, a reduction of only 0.12 % is reached. But again, the spread is quite large for individual customers, with values ranging from 0 % to 0.92 %.

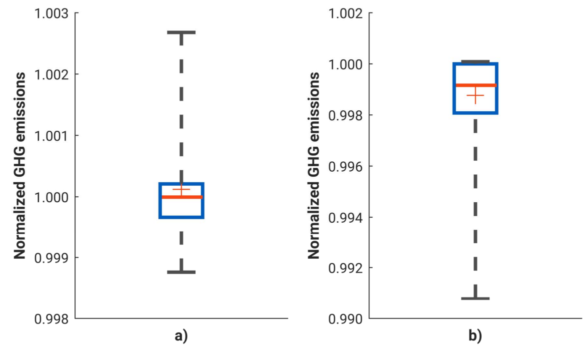

Figure 8. Reduction of GHG emissions for best rate

Therefore, the assignment of individual rates for each customer is also examined here. The resulting distributions are depicted in fig. 9a and 9b for all possible rates and restriction to three rates, respectively. In the first case, the reduction can be slightly improved to 0.14 %, for the reduced set of rates the result is 0.13 %. This shows that time-of-use rates of the described structure cannot be recommended for this specific application, since the improvements are almost negligible and do not justify the effort. However, this conclusion only holds on a short-term perspective, since the potential effects on the generation mix are not considered.

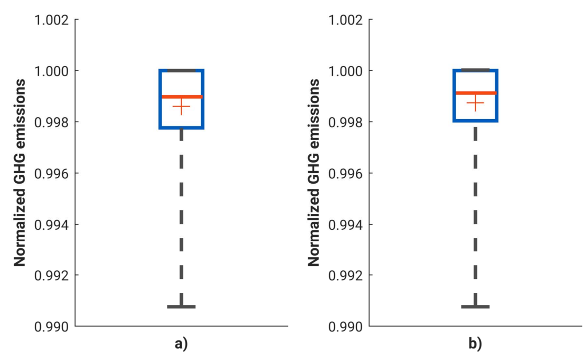

Figure 9. Reduction of GHG emissions for individual rates

Fig. 10 again shows the resulting mean daily load profile in comparison to the original one without load shifting. Similarly to before, appliance operation is delayed from the evening into the night, but in this case, the ideal operation time seems to be a bit later. The similarity also suggests that the goals of reducing energy purchase costs and GHG emissions might be compatible and reachable with the same rates (cf. subsection 5).

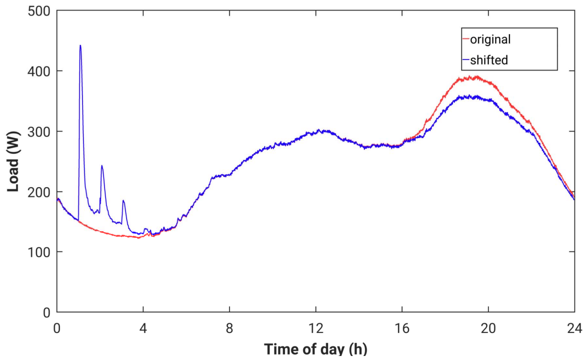

Figure 10. Resulting mean daily load profile for 3 rates

3) *Peak load*

Fig. 11a contains the simulation results for peak load and all simulated rates. For the best rate choice, a considerable reduction of 9.66 % is achieved. This can be a substantial contribution to grid relief measures. Fig. 11b shows the results per individual customer. Most customers' peak load remains unchanged, whereas some reach almost 30 %. On the downside, there are also customers where individual peak load increases. However, since the objective is to reduce the total peak load, the measure can be considered quite effective. For the same reason, the assignment of individual rates is not considered here.

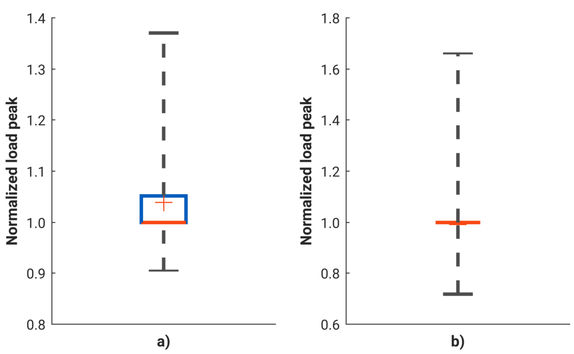

Figure 11. Reduction of peak load for best rate

The resulting mean daily load profile is depicted in fig. 12. As for the previously examined applications, the main difference to the original profile is a shift from about 4 to 10 pm to about 0 to 4 am. The mean daily profile evinces a new peak at midnight, which seems to be worse than the original one. This is not the case, since the actual peaks in the evening hours of the original load are smoothed out by the averaging process.

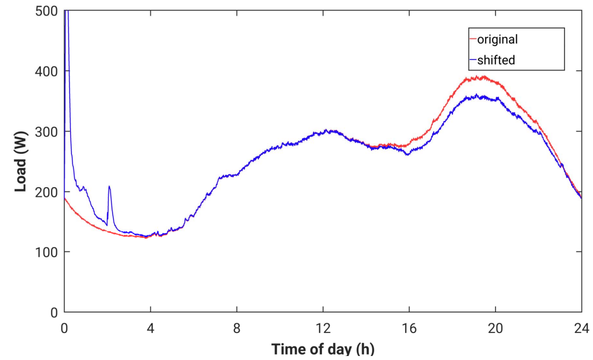

Figure 12. Resulting mean daily load profile for best rate

4) *Photovoltaics peak*

The results for the PV peak are depicted in fig. 13. As before, the correct rate choice is critical for sound results, since there are also worsening ones. In the best case, the negative load peak of PV generation can be reduced by 6.12 %. Again, individual rates are not considered, since the focus is on improvement of total load, not on individual customers' behavior.

The main daily load profile (fig. 14) with shifting differs considerably from the previous applications. Since the peak of PV generation is around noon, operation times from morning hours between 7 am and 12 pm are delayed to match this peak, which improves direct consumption and avoids negative load. The different pattern compared to the other applications indicates that this goal might be competing to the other ones.

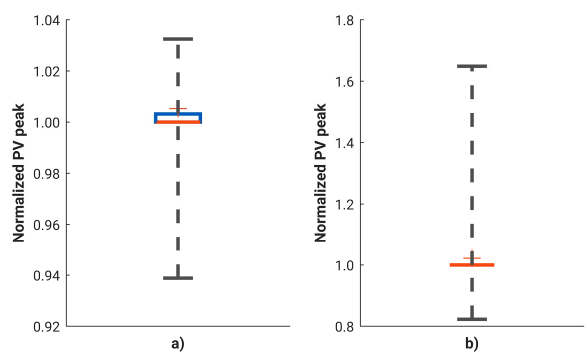

Figure 13. Reduction of PV peak for best rate

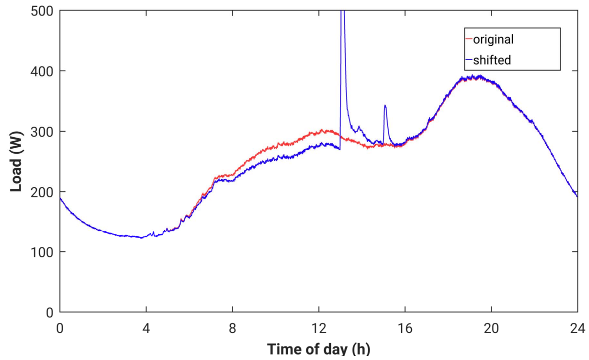

Figure 14. Resulting mean daily load profile for best rate

5) *Multiple applications*

The observation of deviating shifting processes depending on the application leads to the question of compatibility of different goals. In order to analyze this, the best rate choice for each of the four applications is applied and the effects on the three other ones are evaluated. The results are given in Table 1.

TABLE I. RESULTS FOR MULTIPLE APPLICATIONS

Best rate for	**Effect on**			
	Purchase	***Emissions***	***Peak load***	***PV peak***
Purchase	−1.29 %	−0,10 %	−9.66 %	+0.32 %
Emissions	−1.26 %	−0.12 %	−8.96 %	0.00 %
Peak load	−1.29 %	−0.10 %	−9.66 %	+0.32 %
PV peak	−0.21 %	−0.02 %	+7.10 %	−6.12 %

The numbers show that optimization for purchase costs and peak load have strong synergies, since the values are identical. This means that both goals can be reached with the same rate. Moreover, the reduction of emissions in these cases is almost as high as with the optimal rate, so these applications do not seem contradictory. The emission-optimized case confirms this, as purchase costs and peak load are considerably reduced as well.

However, the results for PV peak suggest a problem, since both the effect of optimized rates for the other applications on PV peak and the effect of the PV-peak-rate on the other ones are (almost) nonexistent or negative. But this is misleading, since the additional PV generation also affects purchase prices, emissions and load. Therefore, this comparison does not yield valid results.

IV. Conclusion and Outlook

The discussed methodology can be successfully used in order to simulate the effects of time-of-use rates in the retail electricity market and yields plausible results. The extensive data analysis and pattern recognition for individual customers allows identifying tailored rate models for different applications and goals.

The results show that time-of-use rates can be applied to significantly reduce grid load at discrete events. However, for these effects it would suffice to incentivize only behavioral changes at specific points in time, which means time-of-use rates might not be the ideal choice, but demand charges or critical peak pricing are to be preferred. The potential reductions of energy purchase costs and GHG emissions are rather small to negligible. This also shows that the considered rate structure is not optimal, since it does not adapt to short-term requirements like unusual peaks in the wholesale market prices or high shares of renewables in the market. Therefore, alternative rate structures should be considered for future investigation [13].

The computational effort of the proposed simulation method is quite high. The approach of simulating the effect of all considered rates within the given structure constraints is possible here, but cannot be applied for more sophisticated rate structures due to limitations of memory and computation time. Thus, an optimization algorithm for this nonlinear problem has to be developed in order to find the optimal rate parameters with reasonable effort.

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