EVALUATING TIME-OF-USE DESIGN OPTIONS

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EVALUATING TIME-OF-USE DESIGN OPTIONS

Research in Progress

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Abstract

Information systems in future smart grids will expand the capabilities of the power system through new services and control options. In this context, dynamically updated time-of-use (TOU) rates can be a building block for creating effective and robust pricing schemes in future retail electricity markets: On the one hand, they are better suited to match market dynamics and uncertainties than static, linear tariffs; on the other hand they mitigate the complexity arising from hourly real-time prices. Hence, the proper design of these dynamic rates requires managing the trade-off between complexity and efficiency.

To this end, careful tuning of the rate complexity with respect to variability (number of time zones) and dynamics (frequency of rate adjustments) is necessary. This challenges calls for efficient decision support that allows energy retailers to identify and implement promising rate designs. A framework to determine, analyse and compare a set of rate designs featuring different structural and dynamic design options is presented in this paper. This approach is illustrated using an exemplary scenario based on empirical electricity price data.

Keywords: Time-of-Use Pricing, Smart Grid, Optimization and Decision Support.

1 Introduction

In future smart power grids, the availability of detailed customer-level from smart meters facilitates the design of appropriate coordination mechanisms (Ramchurn et al., 2012). The introduction of dynamic time-of-use (TOU) electricity rates offers utilities opportunities to improve their product portfolio through new products, differentiation and customer segmentation. The importance of innovative pricing schemes in the electricity sector is described, among others, by Parmesano (2007).1 In demand side management systems, dynamic electricity rates can improve system efficiency with respect to reliability and procurement costs (Feuerriegel et al., 2012). Furthermore, time-differentiated billing allows greater transparency with respect to the impact of generation costs for the formation of retail electricity prices. Therefore, they achieve an increased coupling between costs and prices which may also improve the fairness of retail electricity pricing (Faruqui et al., 2010).

1 There are various application scenarios of time-of-use pricing in other domains. For an IS-related example, Saure et al. (2010) apply TOU rates to improve the utilization of cloud computing services. Sen et al. (2013) refer to it as Time-of-Day pricing in their survey of smart data pricing regimes.
A central design component for real time-varying rates is the amount of temporal variability, i.e. the number of tariff time zones per day and the frequency with which prices are updated. Clearly, a tariff with many time zones which is constantly updated instantiates the theoretic benchmark considering its ability to reflect the system state (cf. real-time spot pricing as proposed by Bohn, 1982). However, this argument ignores the behavioural and customer acceptance-related dimensions of varying levels of pricing complexity. Dütschke and Paetz (2013) find that stable tariffs with a limited number of time zones will attract a higher customer acceptance than more complex ones. Woo et al. (2008) argue that attaining customer acceptance is key to realizing a successful smart grid and demand side management implementations. Similarly, recent energy informatics publications (Watson et al., 2010; Feuerriegel et al., 2013) have put forward the importance of determining the optimum level of information granularity in smart energy systems. Consequently, when determining innovative electricity pricing schemes, suppliers need to trade-off benefits from more dynamic tariffs against customer acceptance.

Until now, smart grid research has focused on establishing benchmark results under real-time pricing regimes. Our research seeks to guide decision-makers with respect to the optimal design of electricity rates. Varying rate update intervals and different rate zone number give rise to a multitude of design options. We characterize and formalize various design options, determine an efficient optimization approach and compare the effectiveness of different designs. In particular, we provide answers to the following two research questions:

- What is an appropriate decision framework for determining variable electricity tariffs?
- What is the interplay between the number of rate zones and the update frequency of variable electricity tariffs?

To this end, we propose an evaluation approach and determine the efficiency impact of different design options. The remainder of this paper is structured as follows: Section 2 describes the integrated rate design and evaluation approach which can be seen as a first step towards effective decision support for electricity retailers. Subsequently, Section 3 applies this approach to an example scenario based on empirical electricity market data. Finally, Section 4 concludes and provides an overview of future research opportunities.

2 Decision support for time of use rate design

Setting out to design appropriate TOU rates, we need to acknowledge relevant design options and constraints as well characterize the underlying design goal. Subsequently, the rate optimization and evaluation are described. Figure 1 illustrates how the different elements interact in the context of our research framework. While we do not explicitly model customer acceptance in this paper, it influences both rate design constraints (e.g. ruling out very complex rate designs in the first place) and the rate evaluation process (providing a customer-focused evaluation criterion).

![Rate Design and Evaluation Framework](image-url)
2.1 Design options and constraints

A valid TOU rate structure is characterized by a set of rate zones and thus needs to additionally reflect underlying rate requirements. Depending on the concrete situation, the rate designer has different options and requirements to consider. The rate structure describes the concrete shape of an individual TOU rate specification. Design options include the number of rate zones, the start as well as end times of the rate zones and the price level of the rate zones. We will typically refer to the number of rate zones as the rate granularity $Z$ of a tariff specification. Furthermore, TOU rate design needs to account for constraints related to the customer base and the regulatory environment. Exemplary constraints would be price ceilings, price jump limitations (period differentials must not exceed certain levels), symmetric zoning requirements (period lengths must not differ) or limitations on rate granularity (maximum number of rate zones). Besides the structural properties, rate design also features dynamic design options. Modern smart metering systems facilitate dynamic rate updates, i.e. switching the rate design under a current contractual relationship. We consider two scenarios for implementing rate dynamics, different updating intervals (e.g., monthly, weekly or daily) and specification of different rate designs for distinct day types (e.g., weekdays vs. weekends/holidays).

2.2 Rate objectives

Assessing the quality of a given rate requires the specification of an appropriate objective function for evaluating different rate scenarios. In certain cases, the latter may require the introduction of further constraints to ensure rate validity. Following Parmesano (2007), the underlying rationales for using TOU rates vary. Table 1 provides a selection of typical coordination goals with the corresponding objective function.

These objectives facilitate the quality assessment of rates and provide a base for optimal design approaches of custom rates. Focusing on the establishment of a functional framework for the design of customized TOU rates, we only illustrate the exemplary case of procurement cost matching in the following. This choice allows us to abstract from explicit demand modeling which would require a large number of additional ad-hoc assumptions concerning the functional specification of demand. It should be noted that the results obtained are fairly robust towards changing objective functions.

<table>
<thead>
<tr>
<th>Rate Objective</th>
<th>Objective function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimizing load peaks (grid stability focus)</td>
<td>$\min \left( \max(x_t) \right)$</td>
</tr>
<tr>
<td>Profit maximization (strategic pricing)</td>
<td>$\max \sum_{t} \left( p_t - EEX_t \right) x_t(p_t)$</td>
</tr>
<tr>
<td>Maximization of renewable generation usage (green grid and sustainability)</td>
<td>$\max \sum_{t} \min \left( RES_t , x_t \right)$</td>
</tr>
<tr>
<td>Procurement cost minimization or cost matching (financial risk management):</td>
<td>$\min \sum_{t} \left</td>
</tr>
</tbody>
</table>

*Table 1. Overview of rate objectives ($x_t$ load at time $t$, $p_t$ rate level at time $t$, $EEX_t$ = spot price on power exchange at time $t$, $RES_t$ = renewable generation at time $t$)*

2.3 Rate Design

Having established the multitude of design options available for the customization of TOU rates, we are interested in guiding the decision-making process for determining an appropriate tariff
specifications. To this end, we need to be able to efficiently derive alternative rate structures with varying rate granularity and update frequency properties. Subsequently, we want to assess and compare the quality of these competing design options.

Traditionally, the literature addressing TOU rate design (see for example Oren et al. 1987, Celebi and Fuller 2007 or Saure et al. 2010) uses exogenous assumptions on the rate structure (i.e. number of rate zones and switching times). Hence, these models do not provide guidance for suppliers seeking to develop custom rates (e.g., for marketing or hedging purposes). For example, Reiss and White (2005) empirically derive a demand function for electricity and subsequently test the effect of introducing a specific TOU rate with five zones. Ahlert and van Dinther (2009) require TOU rates to have symmetric zoning where all rate zones are of equal length which again limits the freedom of the rate designer. On the other hand, Flath (2013) proposes an alternative approach relying on a unified optimization model for joint, endogenous derivation of both the rate structure and the price levels using a mixed-integer problem (MIP). Within the optimization, rates are shaped by a combination of binary jump indicator decision variables and continuous decision variables specifying the jump magnitude. Appropriate constraints enforce rate validity while optimizing against an appropriate objective function. The usage of industry-grade optimization tools (e.g., IBM ILOG CPLEX or Gurobi) facilitates fast solving and easy integration into data management systems. This allows to embed the optimization routines within dynamic decision-making contexts, e.g., to reflect sudden changes of the availability of renewable generation. This way, TOU rate dynamics can be increased as discussed above.

2.4 Rate Evaluation

Given its modeling flexibility, we adopt this MIP design approach to generate sets of competing TOU specifications. For modeling details we refer to the original reference. In the following analysis we rely on the fact that the MIP approach determines valid and optimal TOU rate structure. By varying design requirements (e.g., rate granularity, updating schemes) we can populate rate sets to be analyzed subsequently. Figure 1 visualizes the structure of such optimally determined rates with different granularity and updating regimes.

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**Figure 2. Illustration of optimal rate structures**
Given the acceptance results reported by Gerpott and Paukert (2013) and Dütschke and Paetz (2013), rate decision makers (energy suppliers, regulators) will be interested in identifying efficient “rate complexity habitats” – i.e. rates that achieve a good level of load coordination while retaining a complexity level that is accepted by customers. To measure the coordination efficiency of a given rate, we reuse the objective function of the rate optimization problem and determine the efficiency value on a daily basis. However, given the dynamic structure of an energy marketplace, the number of evaluation periods will often greatly exceed the number of rate designs. For example, in the case of annual rate updates only a single rate structure is specified for whole year with 365 evaluation days.

In our analysis, we determine rates based on hourly averages over all corresponding scenario hours. We then measure rate quality by evaluating this “representative rate” against all individual realizations. A subsequent graphical or regression-based analysis of quality values for different rate specifications allows identifying relevant efficiency levers for a given rate design scenario.

3 Exemplary Evaluation

This section serves to illustrate the results from customized TOU rate design. We look at the structure of the rates obtained for different $Z$ values over various updating horizons in a well-defined example scenario. Furthermore, we quantify the efficiency gains that can be achieved by increasing the number of rate zones. Specifically, we consider the case of an electricity broker with procurement costs based on German EPEX spot prices from 2012. We focus on a scenario with hourly price adjustments and a rate time horizon of one day, i.e. a maximum of 24 possible rate zones. In lieu of an explicit demand representation, we apply the cost-matching objective (see last row of Table 1) to illustrate the efficiency potentials of customized TOU rate design. This objective corresponds to the task of an electricity broker aiming to minimize risk when buying and selling electricity. We choose this objective as it requires only a very limited set of assumptions on costs (price scenarios) and the specific objective function (absolute deviation of price and cost level). In the evaluation, our rate efficiency measure is then given by the average hourly matching error between spot and retail price. Concerning design options, we investigate the effect of different rate granularity levels, updating frequencies as well as day type differentiation.

3.1 Descriptive Analysis

The results of the efficiency analysis are illustrated in Figure 2. The figure illustrates the differences between symmetric and asymmetric TOU rate designs for a set of $Z$ values. One can see a fairly large efficiency improvement when going from one to two price levels. As expected, symmetric zoning mostly performs worse than asymmetric zone structures. These differences are less pronounced for more granular rates. Interestingly, symmetric rate designs exhibit distinct non-monotonicities of efficiency in the number of rate zones. The reason for this effect lies in the implicit coupling of jump timing with rate granularity for symmetric rate designs. This is an important result which requires energy retailers to choose rate granularity more carefully in the presence of symmetric zones.
Furthermore, the analysis shows that providing distinct weekend and workday rates improves the cost matching ability of optimally chosen TOU rates. Similarly, rate efficiency is increasing for higher update frequencies. The efficiency gain from increasing the updating frequency is fairly gradual when moving from annual to weekly updating. Roughly speaking, an increase in update frequency by one level improves efficiency by a similar amount as increasing rate granularity from \( Z = 2 \) to \( Z = 24 \) does. Additionally, one can see that efficiency gains from higher rate granularity stagnate around \( Z = 8 \) without daily updating. With daily updated rates, the situation changes and the average matching error is strictly decreasing in the number of rate zones. However, already for \( Z = 12 \) one obtains hourly matching errors below 1 EUR/MWh. Note that these results are obtained under perfect foresight and thus need to be interpreted accordingly.

These results confirm the point raised by Faruqui and George (2002), that “simpler forms of dynamic pricing […] capture many of the economic benefits of real-time pricing […].” Furthermore, they suggest that efficient usage of TOU rates needs to jointly account for rate granularity and update frequency — for infrequent rate updates a rate with few zones (e.g., four) is sufficient, while for daily rate updates more zones should be considered.

### 3.2 Regression Analysis

We want to complement the qualitative results by estimating the parameters of a linear regression model in order to explain the matching errors. Considering the insights obtained from Figure 3, we restrict the analysis to the data set without single zone rates. Similarly, we condense the day groups into a single dummy variable representing either pooled or differentiated day types (i.e. workdays and weekend days separated). This yields the following set of independent variables: Number of rate zones \( Z \), dummy variables \( A_i \) indicating Monthly Updates, Weekly Updates, Daily Updates as well as dummy variables for Symmetric Zoning \( S \) and Differentiated Day Types \( T \). This leads to the following regression equation to explain the matching errors:

\[
y = \alpha + \beta_1 Z + \sum_{i=2}^{4} \beta_i A_i + \beta_5 T + \beta_6 S
\]  

(1)

All independent variables obtain as significant in reducing the matching error (Table 2 in the Appendix) and one achieves a high level of explained variance with an \( R^2 \) of 0.507. Introducing more frequent updating greatly reduces the matching error as well as additional time zones. Also, requiring

\(^2\)Clearly, for daily updating this argument is not applicable as each day is already provided with a distinct rate design.
symmetric zone lengths increases the average matching error by 1.934. Yet, this regression model does not provide any insights concerning the interplay between rate updating and rate granularity. To address this question, we specify a second regression model featuring additional interaction terms between the number of time zones and the various updating frequencies (Table 3 in the Appendix):

\[ y = \alpha + \beta_1 Z + \sum_{i=2}^{4} \beta_i A_i + \beta_5 T + \beta_6 S + \sum_{i=2}^{4} \beta_{i+5} A_i Z \]  

(2)

While this richer model only has a slightly higher \( R^2 \) of 0.523, it sheds light on the mechanics of the matching error with the results confirming our initial hypotheses concerning the interplay between updating frequency and rate granularity: While the number of rate zones remains a significant variable with a negative coefficient, the impact of this variable is much lower with a (non-significant) coefficient value of 0.008 versus a significant coefficient value of 0.165. The explanation for this behavior lies in the interaction term between daily updating and the number of rate zones which obtains highly significant with a coefficient value of -0.210. Therefore, the extent to which rate granularity can contribute to reducing the matching error critically hinges on the updating scheme. Similarly, the efficiency impact of daily updates is less pronounced in the second regression (-5.027 vs. -7.445). Moving to daily updating of rates is thus most effective when combined with a more granular rate structure. The other observations concerning other updating frequency levels, the differentiation of day types and symmetric the zoning requirement remain valid in the richer model.

4 Summary and Discussion

Variable electricity rates with a limited number of time zones can achieve very high efficiency levels similar to more complicated rates. Energy suppliers have three main levers to improve rate efficiency with respect to representing procurement costs — rate granularity, rate update frequency and differentiation of day types. The analysis shows that the most effective first step for achieving better cost representation through retail electricity prices is establishing well-designed TOU rates with two zones. Subsequently, an increase of the update frequency facilitates further efficiency gains. Similarly, rate designs differentiated on a day type base facilitate a reduction of the cost matching error. Additional rate zones beyond two will yield only limited efficiency increases if rates are not updated on a daily basis. Yet, in a daily updating regime higher rate granularity levels help achieve much higher efficiency. We also show that it is detrimental to the efficiency of TOU rates to require symmetric rate zone lengths.

Within the evaluation, rate design was based on hourly means obtained under perfect foresight. Potentially, the presence of uncertainty improves the relative robustness of less granular rate designs. Moreover, uncertainty should further increase the value of an increased update frequency. A case in point is the inclusion of exogenous demand clustering events (e.g., World Cup) which energy suppliers want to react to. We have focused on the cost-matching objective to avoid arbitrary demand specifications. As noted above, the interconnection between demand modelling – determining price elasticity as well as demand functions – and rate design is of special interest, especially when determining rates with a profit maximization objective. Hence, our framework should be applied in conjunction with richer demand models. Complexity modelling approaches such as agent-based simulation could be leveraged to this end (cf. Ramchurn et al., 2012). In the same vein, future research should also investigate the customer side with respect to behavioural dimensions such as the acceptance and response to alternative TOU specifications. Not explicitly modelling the demand side, we cannot directly reflect different acceptance criteria in our analysis. However, we explicitly derive the gains obtained from certain design choices. This provides a base for a comparison with customer acceptance studies in the spirit of Goett and Hudson (2000) or Dütschke and Paetz (2013). Going
forward, it may be especially relevant to explore the behavioural interplay between rate granularity and rate dynamics.

References


Faruqui, A., D. Harris, and R. Hledík (2010). Unlocking the 53 euro billion savings from smart meters in the EU: How increasing the adoption of dynamic tariffs could make or break the EU’s smart grid investment. Energy Policy, 38 (10), 6222-6231.


Appendix

<table>
<thead>
<tr>
<th>Dependent variable: hourly matching error</th>
<th>OLS</th>
</tr>
</thead>
<tbody>
<tr>
<td># of rate zones</td>
<td>−0.165*** (0.003)</td>
</tr>
<tr>
<td>Monthly Updates</td>
<td>−0.975*** (0.296)</td>
</tr>
<tr>
<td>Weekly Updates</td>
<td>−2.498** (0.288)</td>
</tr>
<tr>
<td>Daily Updates</td>
<td>−7.445*** (0.286)</td>
</tr>
<tr>
<td>Differentiated Day Types</td>
<td>−0.479** (0.033)</td>
</tr>
<tr>
<td>Symmetric Zoning</td>
<td>1.934*** (0.044)</td>
</tr>
<tr>
<td>Constant</td>
<td>11.049*** (0.289)</td>
</tr>
</tbody>
</table>

Observations: 26,941
R²: 0.507
Adjusted R²: 0.507

Note: *p < 0.1; ** p < 0.05; *** p < 0.01

Table 2. OLS regression results for matching error (simple model)

<table>
<thead>
<tr>
<th>Dependent variable: hourly matching error</th>
<th>OLS</th>
</tr>
</thead>
<tbody>
<tr>
<td># of rate zones</td>
<td>0.008 (0.012)</td>
</tr>
<tr>
<td>Monthly Updates</td>
<td>−0.713 (0.576)</td>
</tr>
<tr>
<td>Weekly Updates</td>
<td>−1.977*** (0.561)</td>
</tr>
<tr>
<td>Daily Updates</td>
<td>−5.027*** (0.556)</td>
</tr>
<tr>
<td>Differentiated Day Types</td>
<td>−0.479** (0.032)</td>
</tr>
<tr>
<td>Symmetric zoning</td>
<td>1.934*** (0.044)</td>
</tr>
<tr>
<td># of rate zones:Monthly Updates</td>
<td>−0.023 (0.043)</td>
</tr>
<tr>
<td># of rate zones:Weekly Updates</td>
<td>−0.045 (0.042)</td>
</tr>
<tr>
<td># of rate zones:Daily Updates</td>
<td>−0.210*** (0.042)</td>
</tr>
<tr>
<td>Constant</td>
<td>9.048*** (0.556)</td>
</tr>
</tbody>
</table>

Observations: 26,941
R²: 0.523
Adjusted R²: 0.523

Note: *p < 0.1; ** p < 0.05; *** p < 0.01

Table 3. OLS regression results for matching error (model with interaction effects)