Estimating Energy Reduction Amount in the Event of Demand Response Activation: Baseline Model Comparison for the Baltic States

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***Abstract* — Demand response integration in energy markets can provide significant financial saving for grid operators and market participants and promote optimal resource allocation. An important step towards the integration is the introduction of methodology estimating energy transferred via demand response activation event. In essence, a consumption baseline model is a mathematical forecast of the energy consumption pattern that would have occurred in the absence of demand response event. These calculations are then used as the basis for the financial settlement among different market parties – consumers, aggregators, system operators and balance responsible parties. Currently there is no universal consensus on the best consumption baseline model and approaches used, differ wildly even among countries with relatively high demand response commercial activity. The objective of this paper is to compare different consumption baseline methodologies in terms of accuracy and robustness while taking into account the unique challenges within the Baltic region. For the comparative analysis we use hourly consumption patterns of one year for 40 different types of consumers. The analysis suggest that from the consumption baseline models reviewed, UK model performs the best in terms of accuracy and robustness.**

***Index Terms* — Demand response, balancing market, baseline calculations, system balancing, independent aggregation.**

I. Introduction

Demand response service (DR) is a temporal change in consumer's energy consumption due to a reaction to price signals or by other measures [1]. DR is associated with multiple benefits such as increased system flexibility, improved network congestion, cost-effective alternative to grid investments and improved energy efficiency [2], [3].

DR can be broadly divided in two groups: implicit DR and explicit DR. Implicit DR ("price based" DR) refers to consumers choosing to be exposed to time-varying electricity prices and/ or time-varying network tariffs that reflect the real cost of electricity at the time of use and allows the consumer to react to that price depending on their own preferences. Explicit DR refers to a program, where demand competes directly with supply in the wholesale, balancing and ancillary services' markets directly or through the services of aggregators. This is achieved through the controlled changes in the load that are traded in the electricity markets, providing a comparable resource to generation, and receiving comparable prices [4], [5]. Currently, implicit DR in Latvia and Estonia is available to consumers via electricity supply contracts where retail price is linked to the spot price. Starting from late 2017, there is an ongoing DR aggregation pilot study in Estonia, however the explicit DR is not commercially active there or anywhere else in the Baltics. [6]

For explicit DR to become commercially active, a market framework describing the financial settlement among the market parties (such as consumers, aggregators, system operators and balance responsible parties) needs to be developed. Estimate of DR delivered also known as the electricity reduction amount (ERA) is a pivotal part of such a framework. ERA is the difference between the actual consumption that occurred and the forecasted consumption that would have occurred in the absence of DR activation event. This forecast is called a baseline and a method for baseline estimation is called consumption baseline model (CBM) (Figure 1) [7].

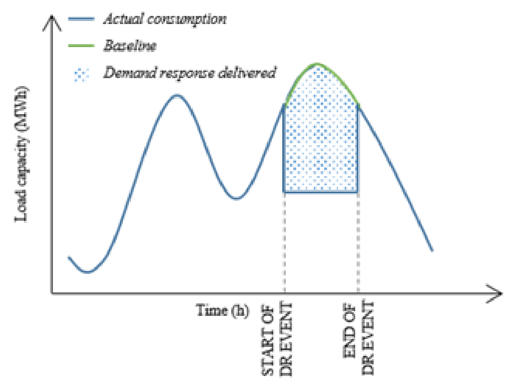

Figure 1. Descriptions of models reviewed

As of now there is no universal consensus on the best performing CBM and even in countries where the DR commercial activity is relatively high (e.g. UK, France, Belgium, USA) the choice of the model tends to be rather fluid, and CBMs are regularly updated to reflect the reduced costs of data collection and processing as well as improved understanding of the underlying processes [2], [4], [5], [7]-[12]. Regional CBM compatibility studies have been performed in USA [7], [10], UK [13], Australia [14] and EU in general [4], [5] among others. When considering a CBM proposal for the Baltic region, we need to take into account the additional challenges regarding the data resolution. Traditionally, DR events for a single metering point can be shorter than 15 minutes. Currently the imbalance settlement period in the Baltics is 1 hour and the metering data that can be used for the financial settlement are collected at the same time resolution [6]. The mismatch between the length of a DR event and the time resolution of available metering data further complicates development of acceptable CBM [11]. The main contribution of this paper is testing CBMs' accuracy and skewness on a lower resolution metering data (using the hourly data that are typically used in Baltics instead of more popular 5-minute or 15-minute resolution usually used in the previous research). Such tests are important because the change in data resolution can have an impact on the relative performance of CBMs.

The rest of the paper is organized as followed – overview of CBMs tested, CBM comparison analysis and Conclusions and further results.

II. Overview of CBM

A. *Characteristics of CBM*

A CBM is used to forecast the consumption in the absence of DR activation event. A well-designed CBM enables grid operators and utilities to measure performance of DR resources and correctly attribute imbalance caused. Such CBM benefits all stakeholders by aligning the incentives, actions and interests of consumers, aggregators, utilities and grid operators, however, not all CBMs can be considered well-designed [11]. A CBM that systematically over-estimates the forecasted consumption will over-value the contribution of the participating DR resource and result in overestimation of positive imbalance for the balance responsible party of the said resource. Conversely, a CBM that systematically underestimates forecasted load will under-value the contribution of the participating DR resource and result in overestimation of negative imbalance for the balance responsible party [11].

Based on the literature review, CBMs are characterized by the following parameters: accuracy (low average expected error); robustness (absence of systematic error in either direction and lack of obvious data manipulation exploitation possibilities for opportunistic market participants) and transparency (market parties can apply the CBM and get the same results as the grid operator) [7], [14]. It is important to note that at times these characteristics are at odds with each other – a very accurate models based on advanced data processing methodologies tend to be fairly complex and non-transparent, while very simplistic models tend to be fairly vulnerable to data manipulation [2], [11]. Accordingly, the choice CBM is ultimately dependent on the relative importance attributed to accuracy, robustness and simplicity. This implied necessity for tradeoffs when designing a CBM for a particular market, at least partly explains the exotic variety of CBMs already in place.

All CBMs can be broadly divided in two categories – day-matching forecast and regression forecast [12]. In the Baltics the concept of explicit DR is still fairly novel and the new market participants (such as independent aggregators) still faces limited enthusiasm from the incumbent market participants. Based on the market maturity and the Baltics market participants' views presented in public consultation summary, it is obvious that a CBM relying on advanced statistic and data processing tools would currently not be feasible [2], [7], [14], [15]. Similar approach can be observed in the EU, where, as of now, only France balancing market has employed long-term statistics-based model, while all other EU states, where CBM is present, has opted for day-matching CBMs [4], [5], [11]. Furthermore, our position on regression based models were further cemented by EnerNOC (2009) that stated that regression models have been rejected in the USA due to the lack of support from the market participants. Accordingly, regression based models are not reviewed in this paper on the basis of not fulfilling the minimum requirements of simplicity parameter [11].

The day-matching CBMs can be further divided in two sub-categories – models using only data from before the DR activation event and models using data from both before and after the DR activation event. In the EU CBMs using only ex-ante metering data seem to enjoy higher popularity [4], [5], which might be linked to the ex-ante/ex-post CBMs being more vulnerable to data manipulation exploits.

B. *Baseline methodology forecast models*

We tested four day-matching CBMs – three of those only use metering data from before DR activation event and one uses data from both before and after activation. Description of the CBMs tested is presented in Table 1.

1. EnerNOC CBM has been used and tested in North America (USA) and is one of the earlier baseline models tested in markets. EnerNOC original variation operates with time resolution of 1 hour. [11]

2. UK model is adopted from the paper by Imperial College London (2014) and for a time was used in the UK. The model originally operates with higher time resolution and the model has been adjusted to the use of hourly metering data [13].

3. Average CBM is the only model in our test that uses both before and after DR activation event data. The model broadly follows concepts present in the CBM employed in Ireland [4], [5].

4. Daily profile CBM is loosely based on the methodology present in Belgium [4], [5]. Similarly, to the Daily profile, the Belgium model does not fully use day-matching approach since only the data from the same day is employed in the CBM. Furthermore, Belgium uses 15 min time resolution.

Based on the paper presented by DNV KEMA (2013) to the basic CBM calculation type, the separate calculation can be applied to align the baseline with the observed conditions of the event day – baseline adjustment method. CBM adjustment method can improve the performance of the model significantly. The factors used for adjustment rules may be based on, but are not limited to: temperature, humidity, calendar data, sunrise/sunset time and/or; event day operating conditions (most widely used factor). There are two main type of baseline adjustments methods:

1. Additive, which adds a fixed amount to the provisional baseline load in each hour, such that the adjusted baseline will equal the observed load at a time shortly before the start of the event period.
2. Scalar, which multiplies the provisional baseline load at each hour by a fixed amount or scalar, such that the adjusted baseline will equal the observed load on average during a window of time shortly before the start of the event period [12].

In our analysis, additive adjustment is used in EnerNOC CBM, UK CBM and Average CBM, while scalar is used in Daily profile CBM (see table I).

TABLE I. TABLE TYPE STYLES

CBM	Short description
EnerNOC	Baseline is equal to the average consumption of 5 corresponding hours with highest consumption within 10 last non-event days. Baseline is adjusted upwards by the average difference between last two hours' actual consumption and their baseline. $$\text{Formula: } b_t = \frac{c_1 + c_2 + c_3 + c_4 + c_5}{5} + \max\left[\frac{c_{t-1} - b_{t-1} + c_{t-2} - b_{t-2}}{2}; 0\right] \quad (1)$$
UK	Baseline is equal to the average consumption of 5 corresponding hours within 5 days with highest daily consumption (out of 10 last non-event days). Baseline is adjusted upwards and downwards by the difference between last two hours' actual consumption and their baseline. $$\text{Formula: } b_t = \frac{C_1 + C_2 + C_3 + C_4 + C_5}{5} + \frac{C_{t-1} - b_{t-1} + C_{t-2} - b_{t-2}}{2} \quad (2)$$
Average	Baseline is equal to the average of consumption one hour before and one hour after the DR event. $$\text{Formula: } b_t = \frac{c_{t-1} + c_{t+1}}{2} \quad (3)$$
Daily profile	Baseline is equal to the consumption within preceding hour multiplied by the fraction of increase/decrease of consumption in the corresponding hours a day before the event. $$\text{Formula: } b_t = \frac{c_{d,\,t-1} * c_{d-1,\,t}}{c_{d-1,t-1}} \quad (4)$$

b_t – baseline at hour t;

c_1 –highest corresponding hourly consumption within 10 last non-event days;

C_1 –highest corresponding hourly consumption in a day with highest daily consumption within 10 last non-event days.

III. CBM COMPARISON ANALYSIS

A. *Data description*

We used hourly metering data that represents annual consumption of 40 randomly selected medium to large electricity end-users from the Baltic region. The set of consumers included different consumption patterns with the hourly average consumption varying from 50 kWh to 3 MWh. In our analysis, we mainly focus on the medium and large consumers due to two reasons: such consumers usually are characterized with higher consumption pattern volatility, such consumers have higher DR potential.

To ensure that the sample is heterogeneous and represents different consumption patterns, correlation analysis was performed for all pattern pairs. The results of the correlation analysis indicated a well diverse sample and indicated that no pattern type is over-represented.

The total number of hours used in the analysis is 8760. Since each model requires different number of days or hours before the event, the number of hours with forecasted baseline differs among the models tested.

B. *Analysis*

Based on the literature review all CBMs analyzed fulfil the simplicity parameter. Accordingly, the objective of the analysis was to quantify each model's accuracy and robustness.

For robustness comparison, we calculated netted mean forecast errors (NMFE) and for the accuracy measurement we used absolute mean forecast error (AMFE). If NMFE is equal (close) to zero it is expected that in long term inaccuracy will not have impact on total amounts of energy transferred – in other words, NMFE measure the extent to which the model is systematically skewed in either direction. AMFE measures the expected deviation in a single instance. As a benchmark for the AMFE we use results from the study covering different CBMs in USA where the model accuracy for models with adjustments ranged from 10-14% [12].

The baseline error was calculated as follows:

$$Er_{BL} = E_F - E_A, \text{ where} \quad (5)$$

Er_{BL} – Baseline error (kWh),

E_F – Baseline or forecasted energy consumption (kWh),

E_A – actual consumption (kWh).

Sample error at a trading interval (t) is calculated as follows:

$$Er_{\%_t} = \frac{\sum_{i=1}^{I} \frac{ErBL_{i,t}}{ErA_{i,t}}}{I}, \text{ where} \quad (6)$$

$Er_{\%_t}$ - baseline error at a trading interval t,
I – number of consumption patterns in the testing sample,
i – consumption pattern.

Accordingly, if the baseline error is above 0 the baseline is overestimated while if the baseline error is below 0, the baseline is underestimated.

NMFE is calculated as follows:

$$NMFE = \frac{\sum_{t=1}^{T} Er_{\%_t}}{T}, \text{ where} \quad (7)$$

NMFE – netted mean forecast error for all trading periods within the sample,
t – trading interval,
T – all trading intervals in the sample.

AMFE is calculated as follows

$$AMFE = \frac{\sum_{t=1}^{T} |Er_{\%_t}|}{T}, \text{ where} \quad (8)$$

AMFE – absolute mean forecast error for all trading periods within the sample.

To estimate the statistical significance of the average accuracy differences observed for both MNFE and AMFE, we run F test for the difference in two variances for all CBM pairs at significance level of 99%. The results indicate that all CBMs' variances are significantly different from each other. We continue with t-test for differences in error means of CBMs. The results are presented in the next section.

C. *Results*

The descriptive statistics of NMFE and AMFE is presented in table II and table III.

TABLE II. NMFE DESCRIPTIVE STATISTICS

	EnerNOC CBM	**UK CBM**	**Average CBM**	**Daily prof. CBM**
SD	33.21%	7.54%	3.52%	6.64%
Variance	$1103\%^2$	$57\%^2$	$12\%^2$	$44\%^2$
Max	727%	66%	182%	389%
Mean	36.6%	0.7%	1.1%	1.1%
Min	1%	-43%	-23%	-100%
Sample	8312	5797	8759	8686

TABLE III. AMFE DESCRIPTIVE STATISTICS

	EnerNOC CBM	**UK CBM**	**Average CBM**	**Daily prof. CBM**
SD	33.15%	6.24%	3.27%	6.49%
Variance	$1099\%^2$	$39\%^2$	$11\%^2$	$42\%^2$
Mean	37.8%	9.5%	4.8%	7.1%
Sample	8312	5797	8759	8686

The density distribution for forecast errors of the CBMs tested is presented in Figure 2.

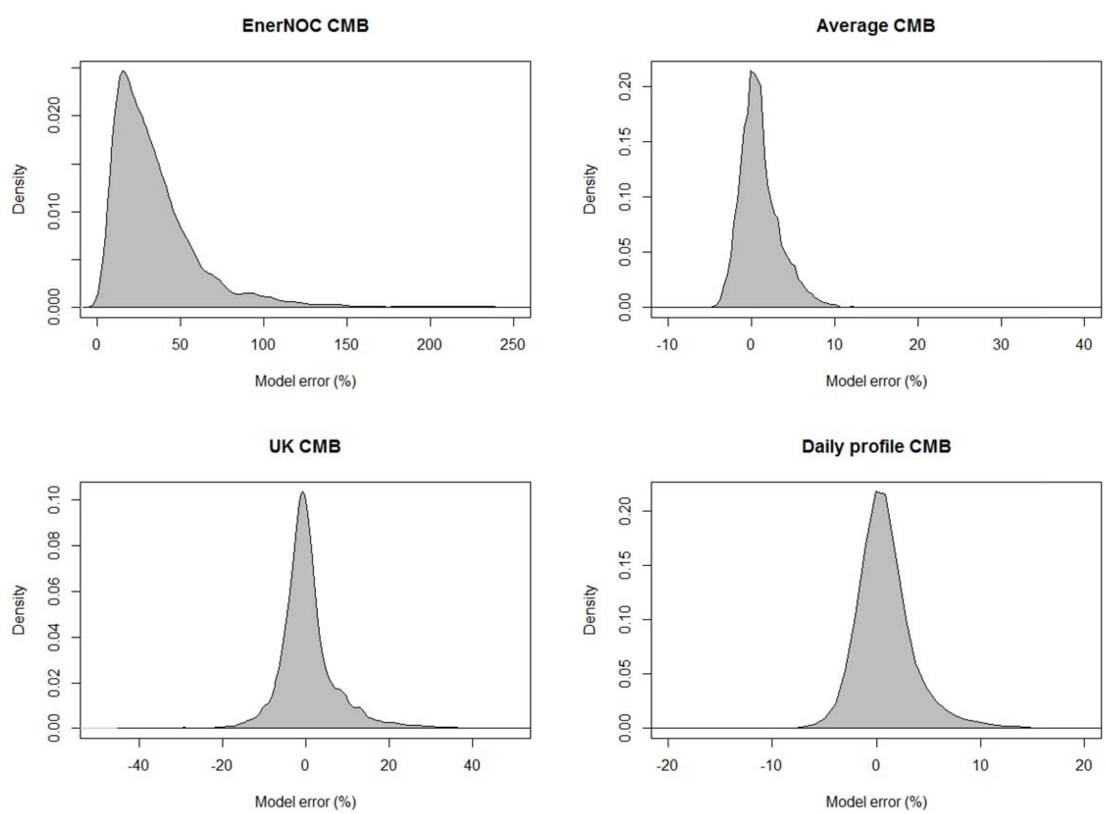

Figure 2. Density distribution for forecast errors of the CBMs tested

The results of the t-test for the mean difference for the model pairs for NMFE and AMFE values are presented in the table IV and table V accordingly.

TABLE IV. NMFE T-TEST RESULTS

t-value for differences of error means			
	UK CBM	Average CBM	Daily prof. CBM
EnerNOC CBM	95.280***	97.068***	95.691***
UK CBM		3.969***	3.677***
Average CBM			0.366

Note: Significance: ***:1% level; **: 5% level; *:10% level.

The results for the t-test for NMFE indicate that there is no significant difference between NMFE of Average CBM and Daily profile CBM. All other differences are statistically significant at a significance level 1%.

TABLE V. AMFE T-TEST RESULTS

t-value for differences of error means			
	UK CBM	Average CBM	Daily prof. CBM
EnerNOC CBM	72.895***	90.306***	83.059***
UK CBM		-52.781***	-22.906***
Average CBM			-28.738***

Note: Significance: ***:1% level; **: 5% level; *:10% level.

The results for the t-test for AMFE indicate that the CBMs present significantly different AMFE at the 1% significance level.

UK CBM shows the lowest NMFE (0.7%). The results indicate that if this model were applied there would be no substantial long-term inaccuracy of ERA in either direction. The EnerNOC CBM shows the poorest results, which is associated with overestimation of ERA for more than one third of the total energy volume.

Analysis of AMFE indicates that all models expect for EnerNOC CBM perform better than the benchmark value of 10-14% and as such is considered to fulfill the minimum accuracy condition.

IV. CONCLUSIONS AND FURTHER RESEARCH

DR is associated with multiple benefits such as increased system flexibility, improved network congestion, cost-effective alternative to grid investments and improved energy efficiency. These benefits can only be taken advantage of if the DR service delivered can be measured in an accurate and transparent way. In this paper, we attempted to identify the most promising CBM for the Baltic States based on the criteria of simplicity, accuracy and robustness. From the four potential CBMs analyzed the best performing CBM in terms of accuracy and robustness is UK model. The model could be further studied and improved by testing different baseline adjustment methods. Furthermore, CBMs could be tested for systematic biases in specific points of the consumption pattern such as peak/off-peak and ramp up/ ramp down periods.

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