Independent review of BSIS methodologies, models and data

Final draft report for National Grid and Ofgem

Date 12 June 2017

[Redacted version for publication]

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Baringa

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Executive summary

Introduction

- The Balancing Services Incentive Scheme (BSIS) is the main incentive on National Grid as the System Operator (SO) with respect to its external balancing costs.
  - It sets targets for those balancing costs that are within the SO's control (rather than acting as a forecast of the SO's costs).
- Baringa has reviewed the 2017/18 BSIS scheme as an independent third party expert. In performing this role we have reviewed the BSIS Methodologies, Models and data that make up the 2017/18 BSIS scheme.
  - This report presents the findings of our analysis, across the constraint and energy models, as well as conclusions or recommendations that we have
- The 2017/18 incentive scheme is a one year scheme, ahead of a wider review of SO incentives and the SO's role more generally.
  - The methodologies and models for 2017/18 are largely based on those from the 2015/17 scheme, with selected changes made in some key areas to improve accuracy.
  - While our review focussed on to the 2017/18 scheme, some of our comments may be more relevant to the more fundamental review of the SO's incentive schemes for future years.
- The review process has been highly iterative, with National Grid responding to our queries and updating the methodologies and models during the course of our review

Findings and observations #1

Updates for 2017/18

- The proposed methodologies and models for 2017/18 are largely based on the previous BSIS scheme established in 2015. Given the short (one year) duration of this scheme, National Grid's approach has been to make enhancements in selected areas rather than fundamentally review the modelling methodologies.
- The enhancements proposed for 2017/18 can be expected to improve model accuracy (e.g. using more recent demand and boundary ex-ante inputs in the constraints model, and incorporating solar PV in the energy models). However, due to limitations in the availability of comparable data sets, it has not been possible to quantify the likely scale of improvement at this time.

Model choices

- While recognising the overall approach is largely a legacy of earlier schemes, the rationale for choosing the individual models and inputs is not always clear. Regression models are simple, linear models, and the inputs – while often seem intuitively correct – at times fail to be predictive.
- We note that there are instances where National Grid has moved away from regression techniques for 2017/18 (e.g. negative reserve and RoCoF) due to poor model performance. Along these lines, we suggest a more rigorous approach to choosing model types is adopted for future schemes, and that a process be introduced whereby poor results would trigger a review of the model and its inputs.

Findings and observations #2

Adapting to changing market fundamentals

- The BSIS methodologies and models need to be capable of adapting to the evolving energy landscape. To some extent this is achieved by appropriate use of ex-post data inputs, such that the BSIS targets are not dependent on National Grid's ability to forecast, for example, commodity prices or market imbalances. However, particularly in the case of regression models calibrated using historical data, there is also a need to refine and update the models themselves.
- A key market development in recent years has been the rapid deployment of embedded solar PV capacity. Accordingly, National Grid has made a number of changes to the 2017/18 methodologies to account for the growing impact of PV upon system operation. Another market trend relevant for 2017/18 is the changing role of coal-fired generation, and we note some of the energy models make implicit assumptions about coal plant (e.g. as a marginal fuel type).
- Beyond 2017/18, other market trends that may need to be considered for future schemes include new flexibility sources (e.g. batteries and DSR) and increased opportunities for cross-border balancing (e.g. Project TERRE).

Findings and observations #3

Interactions and co-optimisation

- We understand that the actions taken as economic and efficient by the National Grid in the Control Room will often solve multiple requirements simultaneously (e.g. reserve, energy balancing and constraints) . However, the current BSIS methodologies and models segment the costs of system operation into multiple products and services, with limited provision for interactions between them. For future schemes, we would suggest considering the merits of a more integrated model, which would allow for trade-offs and co-optimisation across different SO requirements. Nevertheless, we recognise that an integrated model may face challenges with greater complexity and less transparent cost breakdowns.

Longer term incentives

- For future schemes, the methodologies and models will need to accommodate new products such as EFR
- It may also be appropriate to review the treatment of STOR availability fees and the incentives to trade-off the availability fees of additional STOR volumes against procuring reserve in the BM

Target neutrality and model performance

- We note that there are challenges to setting BSIS targets that are neutral to National Grid actions, for example, due to the use of historical outturn data (reflecting SO actions) to calibrate models.
- Equally, where variations are observed between target and outturn values, it is challenging to distinguish between model inaccuracy and SO under/over efficiency performance.

Findings and observations – Energy models

Model reproduction

- In nearly all cases, we have been able to replicate the regression analysis and coefficients obtained by National Grid (with the exception of a model requiring data filtering pre-regression)

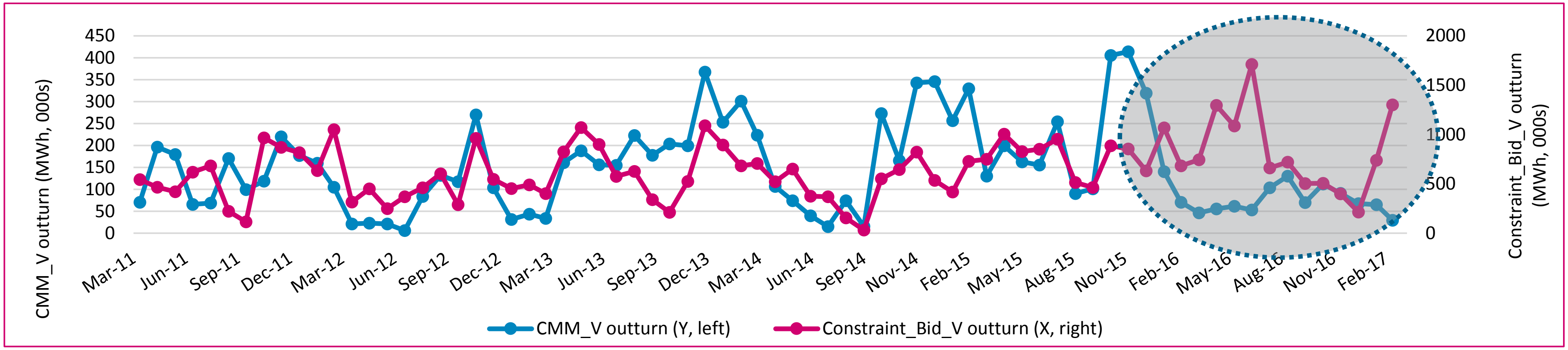
Model fit

- Several of the regression models exhibit a relatively poor fit, as indicated by the R-squared diagnostics. Moreover, in some cases, the model fit appears to have deteriorated since the 2015 update
  - *Examples: Regression models showing a poor fit include OR_V_HH, OR_P_HH and CMM_V with the R-squared for CMM_V falling to 0.08 (from 0.38 in 2015)*
- Deteriorating R-squared values may be caused by a trend shift driven by external factors and indicate that a model may need to be adapted in order to maintain performance
- Nevertheless, despite the decline in some R-squared values since the 2015 update, we should emphasise that it is still important to refresh the model coefficients using more recent data, thereby providing the opportunity for the models to capture recent trends
- Subsequent to our analysis and queries, National Grid has made some model updates and now reports improved Adjusted R-squared values for OR_V_HH and OR_P_HH

Findings and observations – Energy models

Trend shifts

- Reviewing the historical data, one challenge with the regression models is reflecting trend shifts over the training period used for model calibration. Where models fail to pick up trend shifts, we would recommend considering alternative (e.g. shorter) training periods or exploring other model types for future schemes.
  - *Example: In the Constrained Margin Management (CMM) model, the relationship between CMM_V and Constraint Bid Volume appears to break down from January 2016*



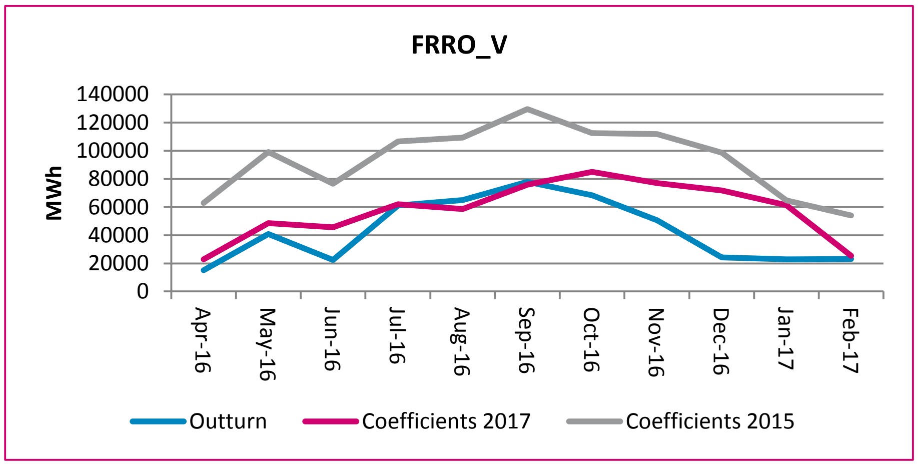
Model complexity

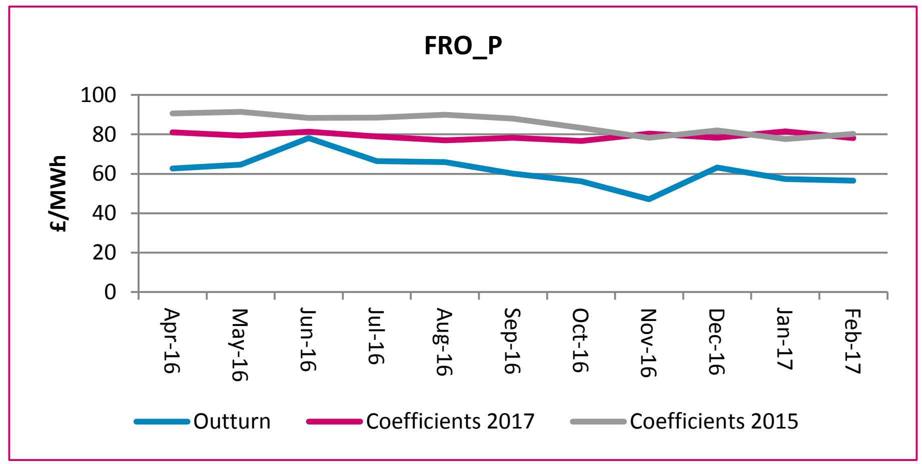
- We would caution against the use of too many nested regressions (regressions within regressions) – this will have the impact of compounding errors. For future schemes, we would suggest “de-nesting” the regression models, with relevant input variables specified directly where possible.
  - *Examples: OR_V_HH is nested within OR_P_HH, CMM_V is nested within CMM_P*

Findings and observations – Energy models

Model coefficients refresh

- For the 2017 scheme, National Grid has refreshed the regression models using historical data from April 2011 to December 2016
- The charts below compare the new (2017) and old (2015) coefficients in the backcast of target costs for the period April 2016 – February 2017 for two regression models, FRRO_V and FRO_P:





- *As would be expected, the new model coefficients perform better than the old coefficients in predicting the 2016/17 outturn, given that data for this period was used for obtaining the new coefficients (model "training")*

Findings and observations – Constraint models

Ex-ante input changes

- The move to 8 week ahead transmission boundary limits (replacing year ahead limits) and 7 day ahead demand data (rather than year ahead) should increase model accuracy by using data closer to real time.
- However, given that the related historical time series were not available to us, we were unable to quantify the expected reduction in forecast errors, and thus also the resultant improvement in model accuracy.

Back-cast analysis

- Based on results from the backcast 2016/17 unconstrained run, the model appears to overstate gas-fired generation at the expense of coal-fired generation, although we would not anticipate this would have a particularly material impact on resulting constraint costs.
- Constrained wind volumes in the backcast 2016/17 run appear to be higher compared to historical data. In discussing this finding with National Grid, we understand the backcast model uses Year Ahead boundary limits which may be differ significantly from outturn limits. Moreover, the PLEXOS model resolves all system congestion by simulated BM actions, whereas, in reality, the SO may take additional measures to minimise constraint costs such as moving outages, trades with wind and intertrips.

Intertrips and discount factor

- We note the inclusion of established intertrips (at least four years old) as part of the modelling baseline is the key reason why National Grid has proposed a significantly higher discount factor in this scheme (0.95) compared to the discount factor used in the previous scheme (0.62). However, for the purposes of this review, we have not seen a detailed breakdown of the potential cost savings attributable to intertrips.

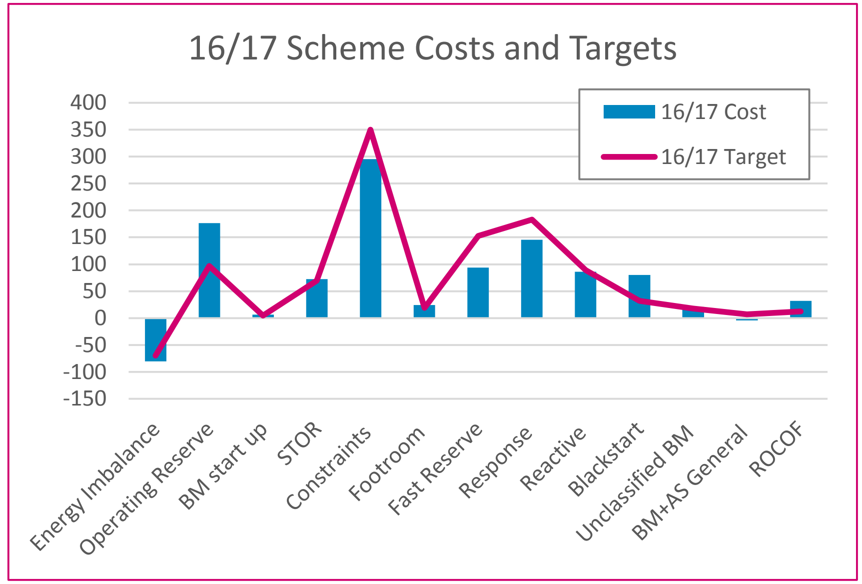
Concluding remarks

- Baringa has conducted an independent review of the methodologies, models and data underpinning the 2017/18 SO incentive scheme, as required by a new National Grid new licence condition
- The proposed BSIS for 2017/18 is a one year scheme, largely based on legacy methodologies and models
- Updates have been made in selected areas to improve accuracy and address identified deficiencies, including:
  - Use of more recent ex-ante data for demand and boundary limits in the constraints model
  - Adjustments for solar PV in the energy models
  - Use of ex-post data for Operating Reserve prices where available
  - Development of a new deterministic model for negative reserve
- These enhancements are expected to improve model accuracy, although it has not been possible to quantify the likely scale of improvement due to data limitations
- The review process has been highly iterative
  - National Grid has responded to our queries and has continued to refine the methodologies and models
  - The majority of our suggested changes to the methodology documents were simply to improve clarity
  - In some cases (e.g. Operating Reserve) National Grid has issued updated models and reported improved fits
- More fundamental changes to the incentives methodologies are expected after 2017/18
  - We have made a number of recommendations of areas for future consideration

Introduction and context

Introduction to SO incentives

- The Balancing Services Incentive Scheme (BSIS) is the main incentive on the System Operator (SO) with respect to its external balancing costs.
- The overall objective is to encourage the SO to be economic and efficient with respect to those costs that it can control
- The BSIS models establish monthly cost targets across a range of areas, linked to different financial rewards. Under the existing scheme, NGET is allowed to keep 30% of any savings below a target, and is unable to recover 30% of any costs above a target.
- The 17/18 incentive scheme also saw the introduction of a new licence condition, which requires a review of BSIS by an independent third party expert. Baringa's role in performing this role, is to review the BSIS Methodologies, Models and data that will make up the 17/18 BSIS scheme
- This year's incentive scheme comes ahead of wider changes to SO incentives to apply from April 2018, and a wider review of the SO's role, regulatory framework and incentives



	Target for 2016/17	Total costs for 2016/17	% under target
Constraints	350	295.3	7%
Energy	613.7	655.09	-16%
Total	**963.7**	**950.39**	**-1%**

Source: March 2017 Monthly Balancing Services Summary. SBR and DSBR costs, and Blackstart IEA allowance excluded. Percentage difference shown as target minus costs, as a proportion of target.

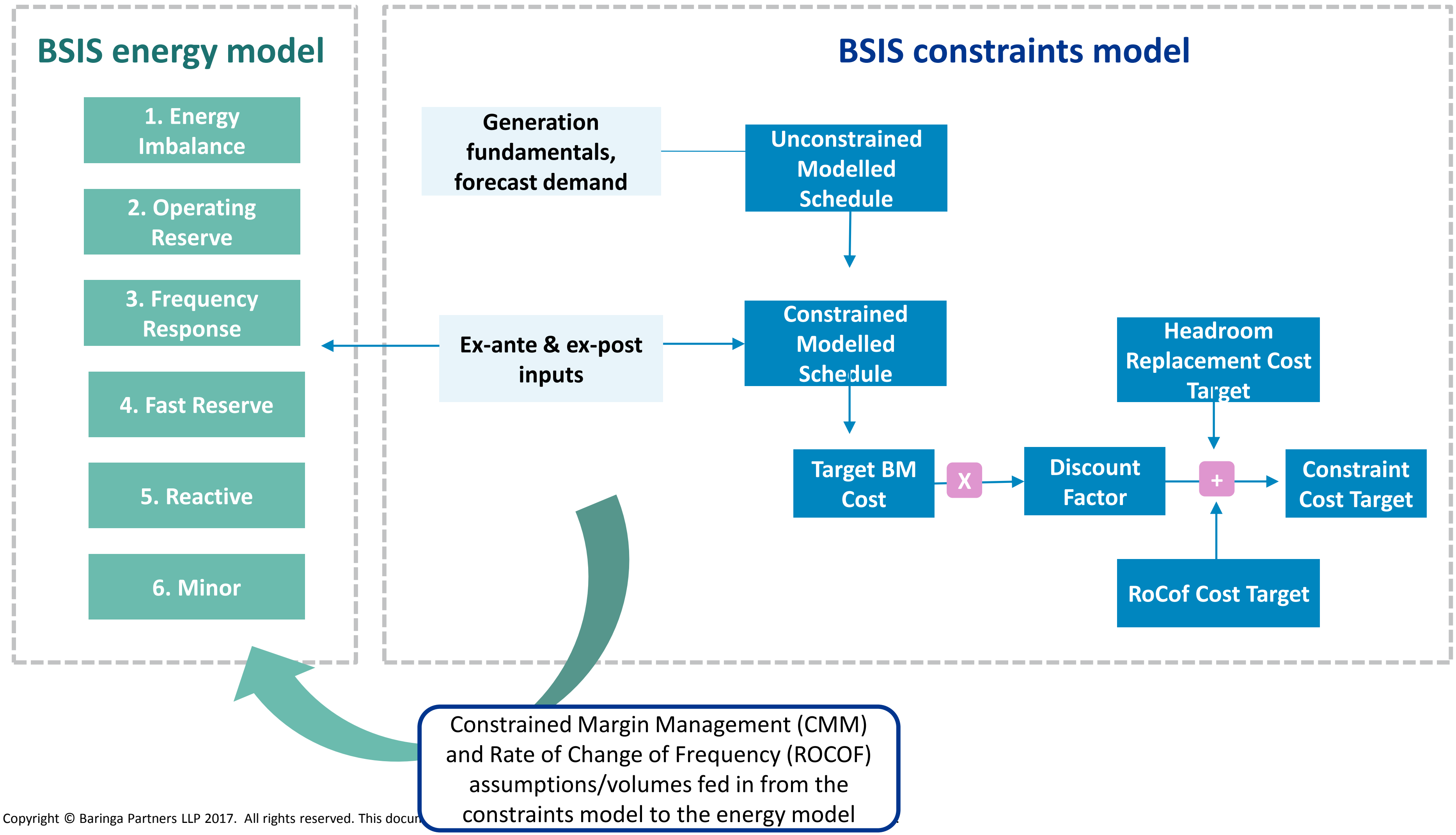
Overview of BSIS methodologies

- BSIS makes use of a set of methodologies and models to set targets for balancing costs, against which National Grid's performance as SO is measured.
- The methodologies are defined in the following documents:

The Statement of the Energy Balancing Cost Target Modelling Methodology	The Statement of the Constraint Cost Target Modelling Methodology	The Statement of the Ex-Ante or Ex-Post Treatment of Modelling Inputs Methodology

- The current models include:
  - BSIS constraints model, a linear optimisation model (PLEXOS) that produces an optimal strategy for the SO to manage constraints in the balancing mechanism (BM), with a discount factor to take account of the availability of non-BM actions
  - BSIS energy model, a set of statistical and deterministic models that use the historic relationship between explanatory variables such as volume to derive a target for the cost of SO's balancing actions.

Overview of models



Key changes to 17/18 BSIS methodologies

In addition to a refresh of coefficients, a number of changes were made to the methodologies

Area		Overview
Energy	**Negative Reserve**	Fully revised model, linked to fundamentals
Energy	**Operating Reserve Cash Price**	New approach to pricing operating reserve that passes through ex-post price when there is an operating reserve
Energy	**Operating Reserve Volume**	Adjustment for solar PV volume
Constraints	**Transmission Boundary Limits**	The modelled network has been developed in line with the network used in operating timescales and the system restrictions anticipated for each year within the scheme period. 8 week ahead boundary limits are used (replacing year ahead limits) which, where relevant, may also reflect intertrip capability
Constraints	**Demand Forecast**	Uses a 7 day ahead forecast of demand (rather than year ahead) based on forecast weather
Constraints	**Discount Factor**	A discount factor of 0.95 is now used, replacing the discount factor of 0.62 that was previously employed
Constraints	**Updated Generation Capacity and Plant Dynamic Parameters**	Updated generation capacity to reflect latest changes with respect to new build and retired capacity (including maintaining a list of new wind and solar connections on a monthly basis). A full recalibration of the unconstrained dispatch against historic running patterns was undertaken to derive plant dynamic parameters (e.g. plant efficiencies, VO&M costs etc.)
Constraints	**Updated Demand Split and Load Participation Factors (LPFs)**	Nodal demand is derived based on the historical percentage of each node's demand in relation to the total GB system demand (using December 2016 data). LPFs are derived from data taken from a period where there was low PV and embedded wind output, and are held constant throughout the year
Constraints	**Western HVDC Link**	Boundary flow limits assessed at 8 weeks ahead of scheduled commissioned date, will have transfer capability assessed with both the HVDC Link available and unavailable, for the relevant boundaries affected
	ROCOF model	New deterministic model, with more granular modelling of largest loss, and half-hourly modelling of demand inertia

Overview of our approach

Baringa

Review of Methodologies

- We reviewed the SO's methodologies and calculations, focussing on the changes and additions to these for 2017/18, and considering whether the calculations accurately reflect the intent of the Methodology
- Where methodologies were re-produced during the process, we reviewed the changes
- Our energy model analysis is based on Version 7 of the methodology (received 11 May) rather than version 8 (received 23 May)

Review of SO Models

- We reviewed the Models to understand how the methodologies have been implemented in the Models and whether this is an accurate representation.
- We analysed the SO's 2016/17 backcast data for the energy and constraints models, to inform how the methodologies have been represented in the Models and whether this is an accurate representation
- We used historic data to reproduce the SO's coefficients

Ex-Ante Data review

- We reviewed the Ex-Ante data to understand how data is used and whether this is an accurate and appropriate representation

Knowledge transfer and query management

- We maintained a log to track queries with the SO's data, models and methodologies. This was shared regularly with the SO, and responses received. Some of these comments resulted in subsequent iterations of the methodologies

Preparation of draft and final reports, and presentation to Ofgem

- Recommendations for change made, where appropriate
- Submission of final query log

Comments on our approach

Assessing an economic and efficient SO

- We assessed whether the Methodologies provide an accurate representation of the SO's costs, but were unable to comment on whether these costs themselves were economic and efficient with the information available to us in this project.
  - We did request information about operational procedures, but have concluded that an assessment of whether the SO is operating economically and efficiently, would require a fuller study of the SO's operational activities and/or benchmarking with international SOs.

Assessing hardcoded figures

- Some figures were hardcoded into the methodologies – for example the discount factor for the constraints model. These values were often based on historic operational experience and/or the NETS Security and Quality of Supply Standard (SQSS) and we did not have access to the data to assess these.
  - We suggest that there is more transparency around these figures in future

Testing alternative methodologies

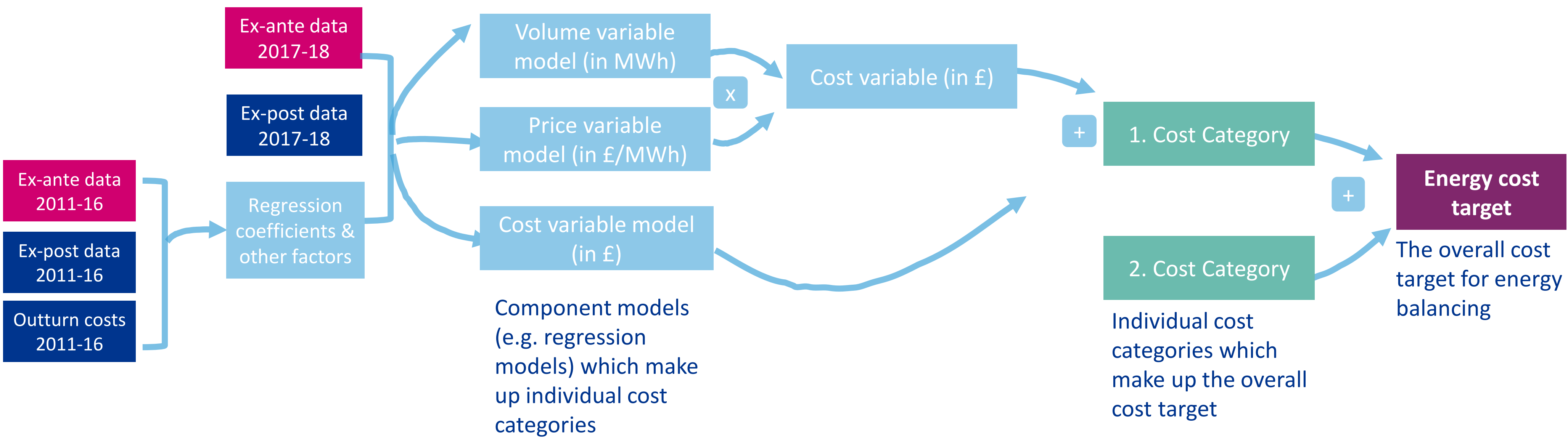
- We had expected to consider alternative methodologies for some cost categories, but our ability to do so was limited by when we received data and methodologies

Overview of methodologies received	
10-Apr	Treatment of Modelling Inputs Methodology
19-Apr	Energy Modelling Methodology 17-18 v5
21-Apr	Treatment of Modelling Inputs Methodology v2
21-Apr	Energy Modelling Methodology 17-18 v6
28-Apr	Constraint Modelling Methodology 17-18 v7
11-May	Energy Modelling Methodology 17-18 v7
23-May	Constraint Modelling Methodology 17-18 v8.3
23-May	Energy Modelling Methodology 17-18 v8

Energy balancing model

Energy methodology – key terms

The energy cost target model comprises a number of cost categories, each of which sets targets determined by a combination of deterministic and regression models



Deterministic approaches

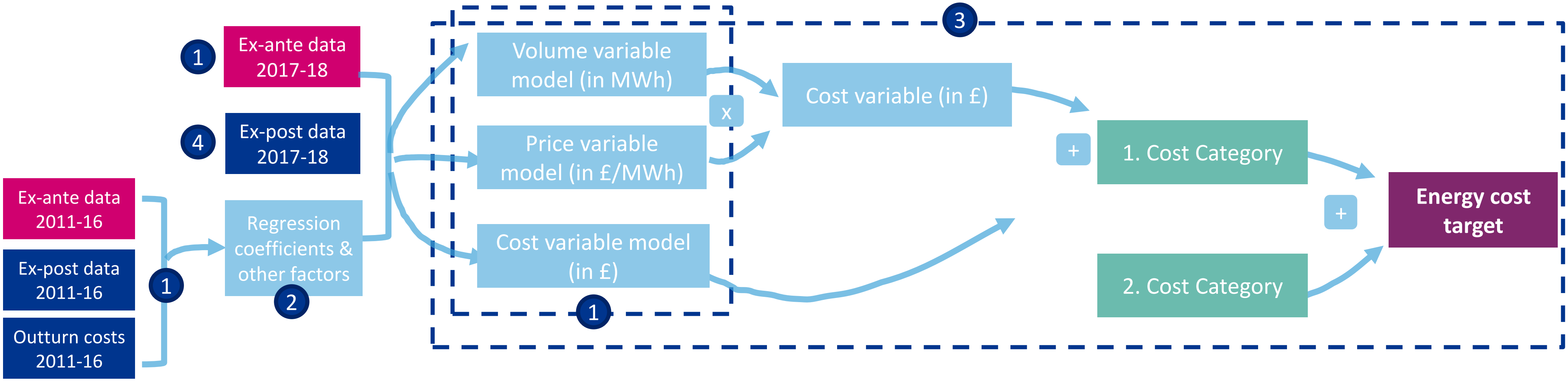
- Used when the SO believes that a target variable (output) can be estimated based on fundamental relationships with other variables (inputs).
- Deterministic approaches have replaced statistical approaches in some cases (e.g. negative reserve) where historical observations are not regarded as a good predictor of future cost drivers and regression models are not appropriate.

Statistical approaches

- Used when the SO believes that a target variable may be predicted approximately from some other variables (inputs) by establishing a mathematical relation, e.g. by building a linear regression model using historical data.
- All the component regression models in the 17/18 scheme have been built using data from April 2011 to December 2016.

Energy methodology – key steps

The energy cost target model comprises a number of cost categories, each of which sets targets determined by a combination of deterministic and regression models



1 | 2 *Before Apr '17* | 3 | 4 *Apr '17 – Mar '18*

1 (i) Calculate 2017-18 ex-ante data, and collect ex-ante and ex-post data from the past years (using data available on 20 March 2017, subject to settlement and reconciliation)
(ii) Review and change component models, where appropriate

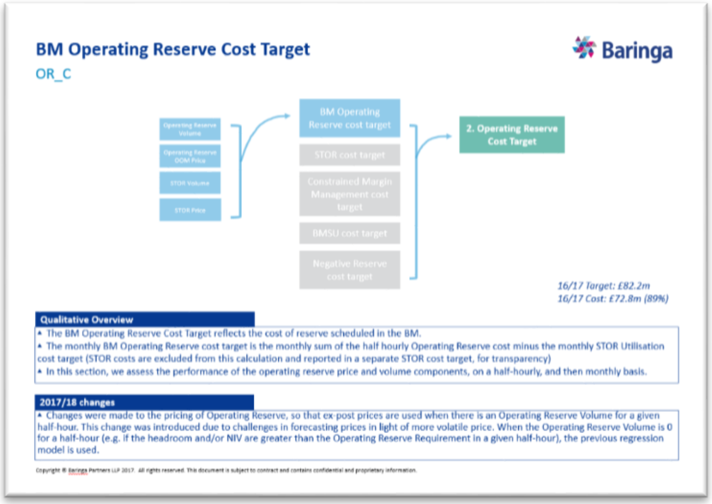
2 Determine / refresh the fixed factors used in component deterministic models and the coefficients of regression models, based on the data collected in Step 1

3 Produce the full backcast for 2016-17 and the skeleton forecast for 2017-18, using the factors and the coefficients obtained in Step 2

4 Collect 2017-18 ex-post data on a monthly basis and feed them into the skeleton forecast produced in Step 3

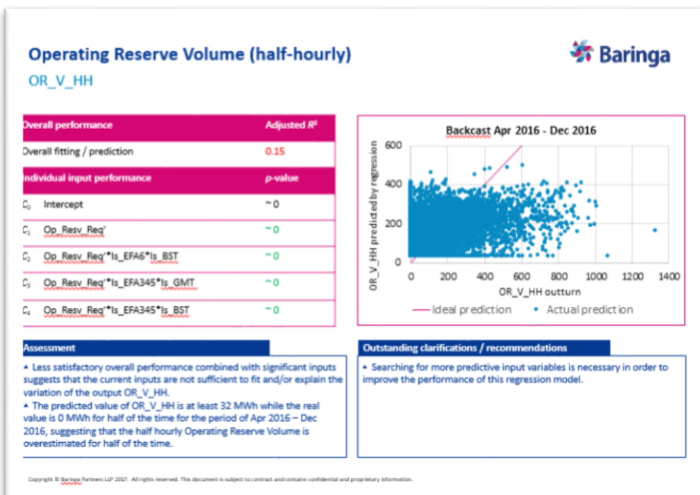
Presentation of our analysis

We provide an overview of each cost category and cost component, before presenting our analysis. Further analysis is presented in the appendices



Overview

- We present an overview of each cost model and the variables that we have analysed
- We present a high-level depiction of the model, with calculations shown in light blue, ex-ante inputs shown in **pink** and ex-post inputs shown in **dark blue**
- This intro page also includes a qualitative overview of the balancing service, with target and outturn costs for the 16/17 scheme, where appropriate.
- We also include an overview of changes made for the 16/17 scheme.



Analysis

- We highlight the adjusted R2 values to show overall fit of the model, and p-values for inputs that we have assessed
- We display the results of our backcast analysis in a graph to show overall fitting
- We provide commentary on the analysis and highlight any relevant recommendations and/or clarifications that are outstanding
- The accompanying query log provides a full list of queries, including those arising from our review of the model implementations

Assessing the models

We assessed the performance of the linear regression models and their individual inputs

Assessing the **overall performance** of a linear regression model:

- R^2 is used to evaluate how good the overall fit of a regression model is where there is only one input / explanatory variable (*X or* X_1)
- Adjusted R^2 is used for the same purpose where there is more than one input / explanatory variable (X_1, X_2, X_3, …)
- The value of R^2 ranges between 0 and 1, while Adjusted R^2 can be negative for poorly defined models
- The closer to 1 the (adjusted) R^2, the better the overall performance of a linear regression model

Assessing the **individual input performance**:

- *p*-value is used to evaluate how significantly an individual input contributes to the regression [i.e. not to the target variable (*Y*) but to its prediction obtained by the regression (often marked by *Y*-hat)]
- The value of *p*-value ranges between 0 and 1
- The closer to 0 the *p*-value, the more significant an individual input
- Usually a *p*-value of 0.05 or smaller is considered statistically significant

We mark:

- **Good** performance in green;
- **Moderate** in amber; and
- **Poor** in red.

Overview of the regression models

Within the Energy Model, values of 16 intermediate variables were predicted using regression

Cost category	Cost sub-category	Model output	Coefficients reproducible?	Overall performance: (adjusted) R^2	Outturn materiality [1]	Under- / over-estimation [1]
2. Operating Reserve	BM Operating Reserve	OR_V_HH	Y [2]	0.15 [2]	Cash cost: £147m [1] OOM cost: £137m	Cash cost: +16% OOM cost: -15%
		OR_P_HH	Y	0.12		
	Short-term Operating Reserve (STOR)	STOR_V	Y	0.81	(N/A)	
	Constrained Margin Management (CMM)	CMM_V	Y & N [3]	0.081 [3]	£46m	-38%
		CMM_P	Y & N [4]	0.74 [4]		
	Balancing Mechanism Start-up (BMSU)	BMSU_C	Y	0.018	£5.8m	-47%
3. Frequency Response	Frequency Response Bid	FRRB_V	Y	0.28	£12m	+74%
		FRRB_P	Y	0.88		
	Frequency Response Offer	FRRO_V	Y	0.46	£9.6m	+32%
		FRRO_P	Y	0.91		
	Frequency Response Ancillary Services (AS)	FRRA_C	Y	0.97 (but please see Slide)	£113m	+12%
4. Fast Reserve	Fast Reserve Bid	FRB_P	Y	0.23	£1.4m	+16%
	Fast Reserve Offer	FRO_V	Y	0.94	£17m	+15%
		FRO_P	Y	0.0045		
	Fast Reserve Ancillary Services (AS)	FRA_C	Y	0.065	£69m	+25%
5. Reactive	-	REAC_Ratio	Y	0.86	(Data unavailable)	

1. Calculated using the outturn data and the backcast results (using the coefficients for 2017-18) for the period of April 2016 – February 2017, except for the BM Operating Reserve cost which only covers the period of April 2016 – December 2016 due to limited data availability.
2. Baringa reproduced the coefficients set out in the Energy Model Methodology v7; the coefficients were subsequently updated in v8. The adjusted R^2 of 0.15 was obtained with the reproduced set of coefficients set out in v7.
3. Baringa reproduced the coefficients set out in the Energy Model Methodology v6; the coefficients were updated in v7 probably due to updates in the input variable Constraint_Bid_V, but no corresponding updated data were received and therefore we were unable to reproduce the new coefficients. The R^2 of 0.081 was obtained with the reproduced set of coefficients set out in v6.
4. Baringa was unable to reproduce the coefficients set out in the Methodology because NG used a filter for pre-processing which is based on data unavailable to us; NG managed to replicate Baringa's coefficients and adjusted R^2 (0.74) that were obtained with unfiltered data.

Regression models: comparison of R-squared values

Both R^2 and adjusted R^2 are calculated - these are set out below. The values used to evaluate the models are highlighted in pink, and less than satisfactory performance highlighted in red and amber.

Model	R^2			Adjusted R^2		
	2015-17 NG	*2017-18 NG*	*2017-18 Baringa*	*2015-17 NG*	*2017-18 NG*	*2017-18 Baringa*
OR_V_HH	0.21	0.15	0.15	0.21	0.15	**0.15**
OR_P_HH	0.14	0.12	0.12	0.14	0.12	**0.12**
STOR_V	0.80	0.83	0.83	0.80	0.81	0.81
CMM_V	0.38	0.08	**0.08**	0.37	0.07	0.07
CMM_P *	0.52	0.44	0.75	0.51	**0.43**	**0.74**
BMSU_C	0.51	0.05	0.05	0.49	0.02	**0.02**
FRRB_V	0.69	0.32	0.32	0.67	0.28	**0.28**
FRRB_P	0.95	0.90	0.90	0.95	0.88	0.88
FRRO_V	0.47	0.50	0.50	0.42	0.46	**0.46**
FRRO_P	0.90	0.92	0.92	0.90	0.91	0.91
FRRA_C	0.99	0.99	0.99	0.99	0.97	0.97
FRB_P	0.01	0.23	**0.23**	-0.0038	0.22	0.22
FRO_V	0.97	0.96	0.96	0.97	0.94	0.94
FRO_P	0.22	0.03	0.03	0.20	0.0045	**0.0045**
FRA_C	0.83	0.09	0.09	0.82	0.06	**0.06**
REAC_Ratio	0.80	0.86	0.86	0.79	0.86	0.86

* CMM_P: different coefficients were obtained because NG used a filter for pre-processing which is based on data unavailable to Baringa; NG managed to “reproduce” Baringa’s coefficients and adjusted R^2 that were obtained with unfiltered data.

Overview of the deterministic models

Baringa

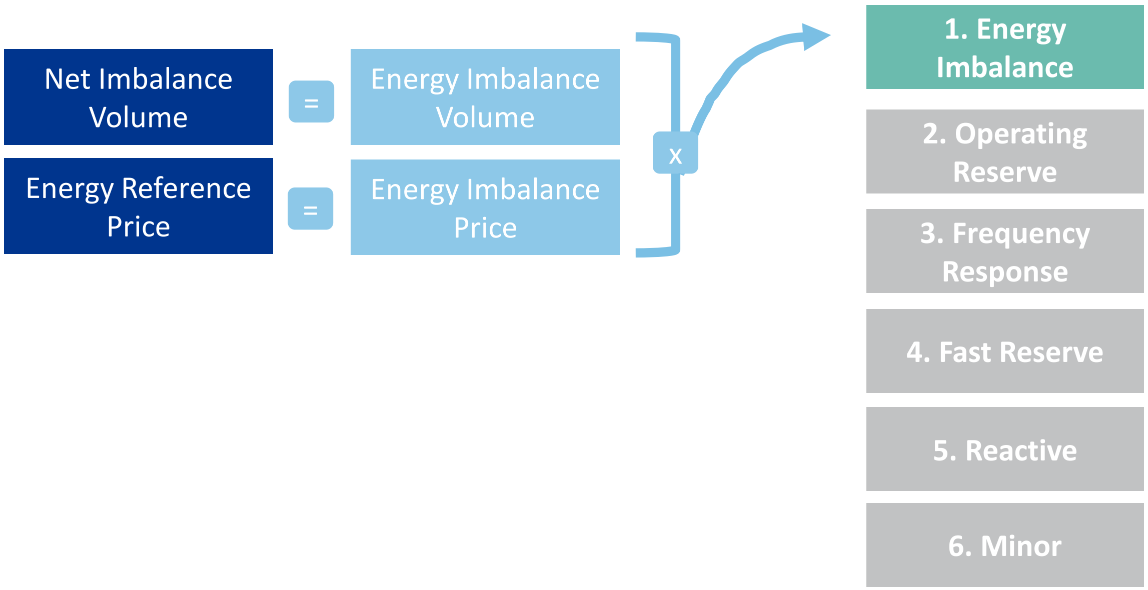
Within the Energy Model, values of 5 major intermediate variables were predicted using deterministic models

Cost category	Cost sub-category	Model output	Coefficients reproducible?	Overall performance	Outturn materiality [1]	Under- / over-estimation [1]
1. Energy Imbalance	-	EI_C	(N/A)	N/A (pass through of net market imbalance costs).	(Data unavailable)	
2. Operating Reserve	Negative Reserve	NR_C	Data unavailable	We are not in a position to evaluate performance of this model, as it was new for the 17/18 scheme.	£24m	-2%
4. Fast Reserve	Fast Reserve Bid	FRB_V	Y	Less satisfactory (please see Slide)	£1.4m	+16%
6. Minor	Ancillary Services (AS) & BM General	AS_BM_C	Y	Prediction by linear regression (by Baringa) gives almost identical results – the corresponding R^2 of 0.33 can be viewed as a good indicator.	(Data unavailable)	
	BM Unclassified	UN_BM_C	Y	Prediction by linear regression (by Baringa) gives almost identical results – the corresponding R^2 of 0.83 can be viewed as a good indicator.	(Data unavailable)	

1. Calculated using the outturn data and the backcast results (using the coefficients for 2017-18) for the period of April 2016 – February 2017, except for the BM Operating Reserve cost which only covers the period of April 2016 – December 2016 due to limited data availability.

Energy Imbalance Model

EI_C



16/17 Target: £-69.7m
16/17 Cost: £-80.4m

Qualitative overview

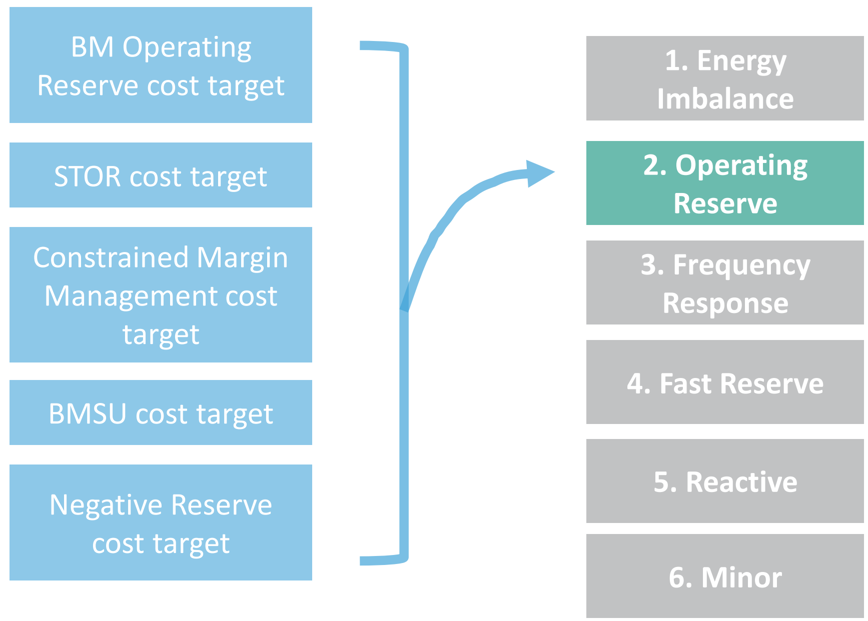
- The energy imbalance cost target concerns the costs that the SO incurs to resolve energy imbalances on the system (i.e. the difference between generation supplied by the market and demand on the system). The cost target is calculated using ex-post values for the net imbalance volume (NI_V) and the Energy Reference Price (ER_P), a price set using an unconstrained schedule of the most economic bids and offers submitted to the BM.
- The revenues from the energy imbalance model are typically negative, as the SO is a net recipient of energy imbalance cashflows (e.g. from revenues from bids in the BM).
- As the volume of imbalance is fed in ex-post, the main variable that affects the energy imbalance cost target is the ERP. This is calculated using an unconstrained schedule of the most economic bids and offers submitted to (rather than accepted in) the BM. This ignores physical characteristics of generators and of balancing the system – and therefore is likely to outturn at a lower price than a volume weighted average of all actions that were actually taken to balance the system when the system was short, and a higher price when the system was long.

17/18 changes

- In response to our feedback, minor changes were made to the methodology to clarify that the Energy Reference Price, rather than the Energy Imbalance Price, is used in this model.

Operating Reserve Cost Target Model

OR_C + STOR_C + BMSU_C + CMM_C + NR_C

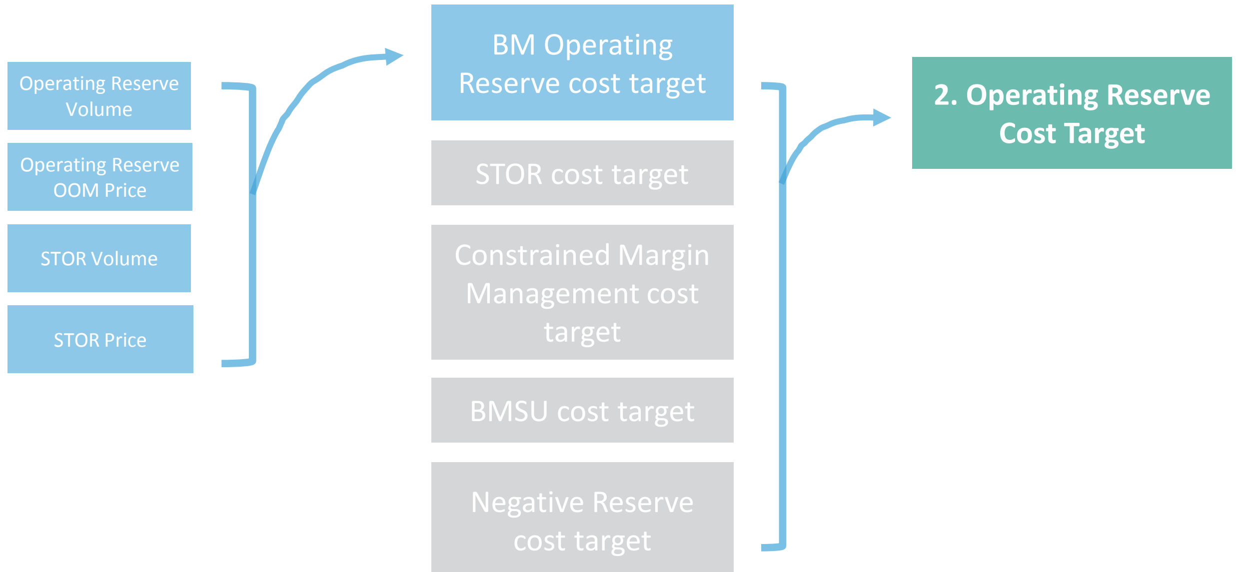


Qualitative Overview

- Operating Reserve is the capacity available to the SO to respond to unforeseen imbalances within short timeframes. The Operating Reserve Cost Target is comprised of five models for different types of reserve that the SO can procure (detailed in the following slides).
- Overall, the Operating Reserve Cost Model performs poorly on a half-hourly basis, but performs better when costs are viewed on a monthly basis.

BM Operating Reserve Cost Target

OR_C



16/17 Target: £72.8m
16/17 Cost: £82.2m

Qualitative Overview

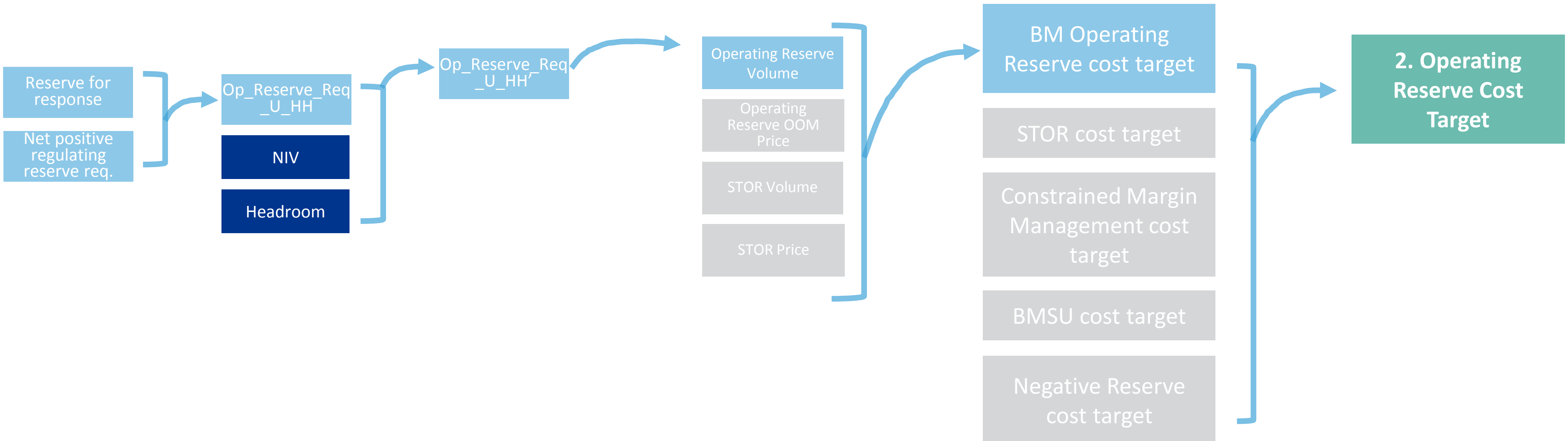
- The BM Operating Reserve Cost Target reflects the cost of reserve scheduled in the BM.
- The monthly BM Operating Reserve cost target is the monthly sum of the half hourly Operating Reserve cost minus the monthly STOR Utilisation cost target (STOR costs are excluded from this calculation and reported in a separate STOR cost target)
- In this section, we assess the performance of the operating reserve price and volume components, on a half-hourly, and then monthly basis.

2017/18 changes

- Changes were made to the pricing of Operating Reserve, so that ex-post prices are used when there is an Operating Reserve Volume for a given half-hour. This change was introduced due to challenges in forecasting prices in light of increased volatility. When the outturn Operating Reserve Volume is 0 for a half-hour, the previous regression model is used.
- An adjustment was also introduced to the operating reserve volume calculation to account for solar PV.

Operating Reserve Volume

OR_V_HH



Qualitative Overview

- The Operating Reserve Volume (OR_V) is the amount of reserve that the SO needs to procure in a given half-hour.
- The Operating Reserve Requirement (Op_Reserve_Req_U_HH') used to set the OR_V_HH reflects a volume determined by the requirement regulating reserve (Net_Positive_Regulating_Reserve_Req_U_H), and the amount of Reserve for response (Reserve_For_Response_U_HH), adjusted for headroom provide by the market and the NIV.
- OR_ V is also used in the calculation for Operating Reserve Cash Price (OR_P_HH), STOR Utilisation Volume (STOR_V) and Frequency Response Bid Volume (FRRB_V)

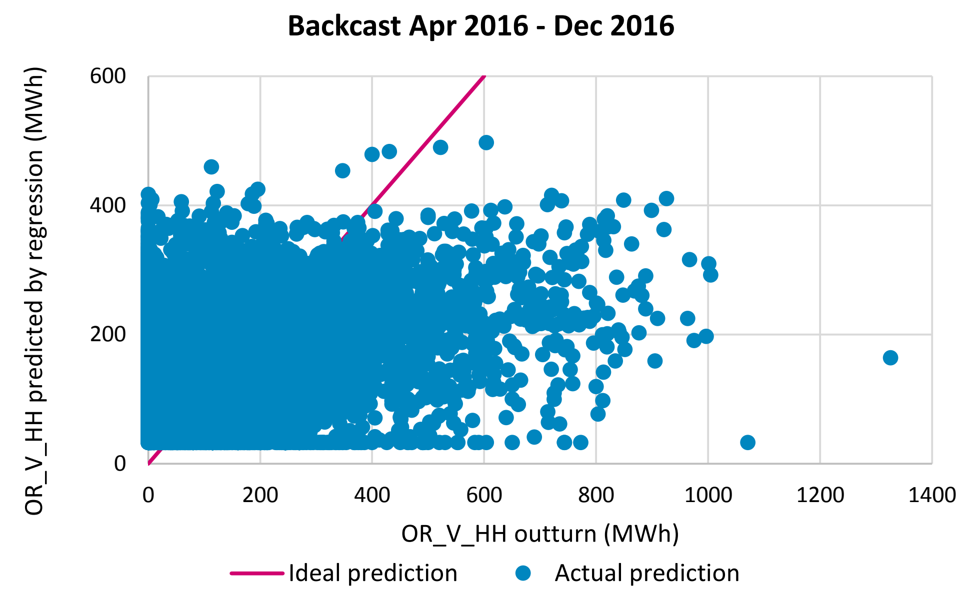
2017/18 changes

- An adjustment to the model was introduced to account for solar PV
- Coefficients in the OR_V_HH regression model were refreshed

Operating Reserve Volume (half-hourly)

OR_V_HH

Overall performance	Adjusted R^2
Overall fitting / prediction	0.15
Individual input performance	***p*-value**
C_0 Intercept	~ 0
C_1 Op_Resv_Req’	~ 0
C_2 Op_Resv_Req’*Is_EFA6*Is_BST	~ 0
C_3 Op_Resv_Req’*Is_EFA345*Is_GMT	~ 0
C_4 Op_Resv_Req’*Is_EFA345*Is_BST	~ 0



Assessment

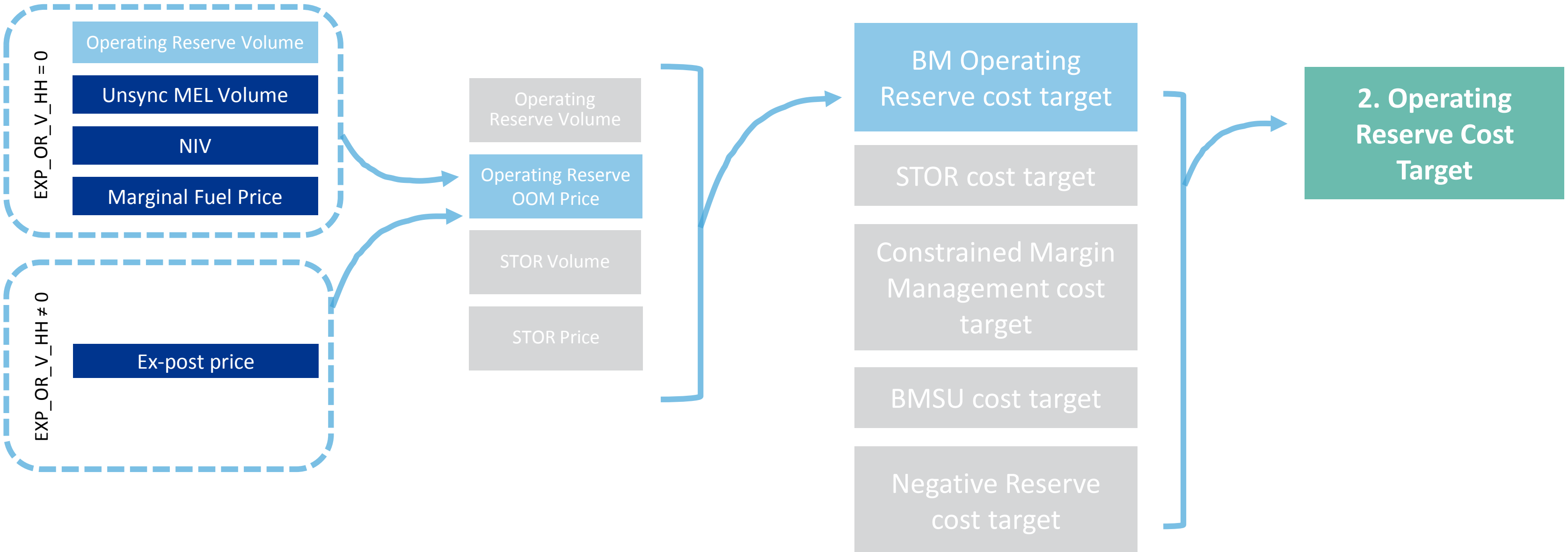
- Less satisfactory overall performance combined with significant inputs suggests that the current inputs are not sufficient to fit and/or explain the variation of the output OR_V_HH.
- The predicted value of OR_V_HH is always at least 32 MWh (the C_0 intercept) while the real outturn value is 0 MWh for half of the time for the period of Apr 2016 – Dec 2016, suggesting that the half hourly Operating Reserve Volume is often overestimated.

Outstanding clarifications / recommendations

- Searching for more predictive input variables is necessary in order to improve the performance of this regression model.
- Subsequent to our analysis and queries, National Grid has made some updates to the OR_V model and now reports an improved Adjusted R^2 of 0.21

Operating Reserve Price

OR_P_HH



Model description

- The Operating Reserve Price represents the price paid to Operating Reserve when it used to balance the system. The Energy Reference Price (ER_P_HH) is subtracted from it, to set the BM Operating Reserve Out-of-money (OOM) Price (OR_OOM_P_HH).
- When there is an outturn Operating Reserve Volume (EXP_OR_V_HH>0) the weighted average of all accepted actions taken for operating reserve is used to set the OR_P_HH. When there is no outturn Operating Reserve Volume for a half-hour a regression model is used.

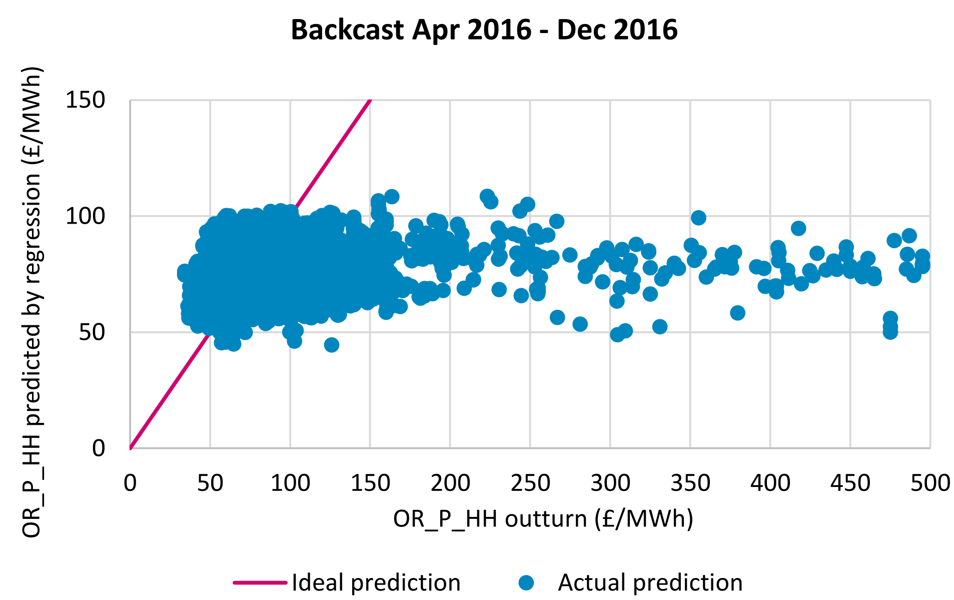
2017/18 changes

- Changes were made to the pricing of Operating Reserve, so that actual Operating Reserve prices are used when there is an Operating Reserve Volume (EXP_OR_V_HH) for a given half-hour. When the outturn Operating Reserve Volume is 0 (e.g. if the headroom and NIV are greater than the Operating Reserve Requirement) for a half-hour the previous regression model is used.
- Coefficients in the OR_P_HH regression model were refreshed

Operating Reserve Price (half-hourly)

OR_P_HH (when EXP_OR_V_HH = 0)

Overall performance		Adjusted R^2
Overall fitting / prediction		0.12
Individual input performance		***p*-value**
C_0	Intercept	~ 0
C_1	Unsync_MEL_V_HH	~ 0
C_2	OR_V_HH	~ 0
C_3	NI_V_HH*Is_EFA345*Is_GMT	~ 0
C_4	NI_V_HH*Is_EFA345*Is_BST	~ 0
C_5	Marginal_Fuel_P_HH	~ 0
C_6	Marginal_Fuel_P_HH*Is_EFA345*Is_GMT	~ 0
C_7	Marginal_Fuel_P_HH*Is_EFA345*Is_BST	~ 0



Assessment

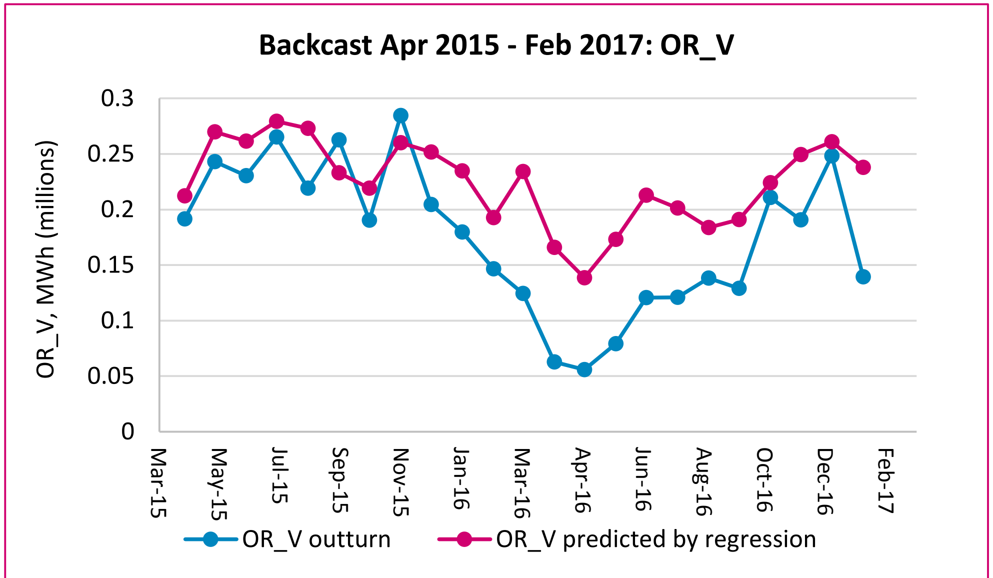
- We assessed the suitability of the regression in predicting the OR_P_HH only in situations when there was no Operating Reserve procured (as ex-post prices are otherwise used).
- Less satisfactory overall performance combined with significant inputs suggests that the current inputs are not sufficient to fit and/or explain the variation of the output OR_P_HH, especially when the real price is relatively high

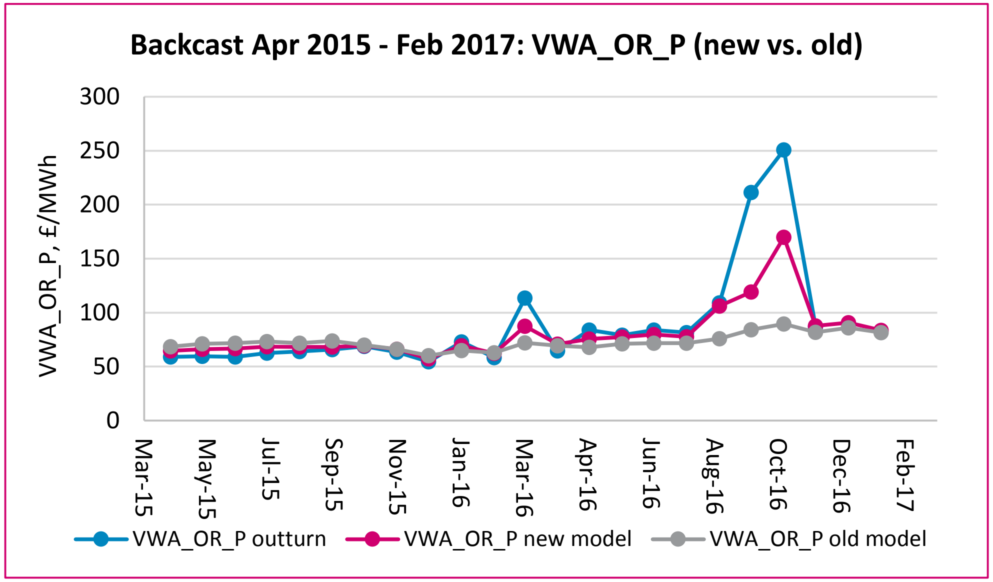
Outstanding clarifications / recommendations

- Searching for more predictive input variables is necessary in order to improve the performance of this regression model.
- Subsequent to our analysis and queries, National Grid has made some updates to the OR_P model and now reports an improved Adjusted R^2 of 0.19
- The marginal fuel price metric was based on coal rather than gas for over 95% of 2016/17, but with recent plant closures, the capacity of coal plant to provide response/reserve services is much more limited. Going forward, it should be considered whether the reference to coal generation costs is still appropriate

Operating volume and operating price (monthly)

OR_V and OR_P





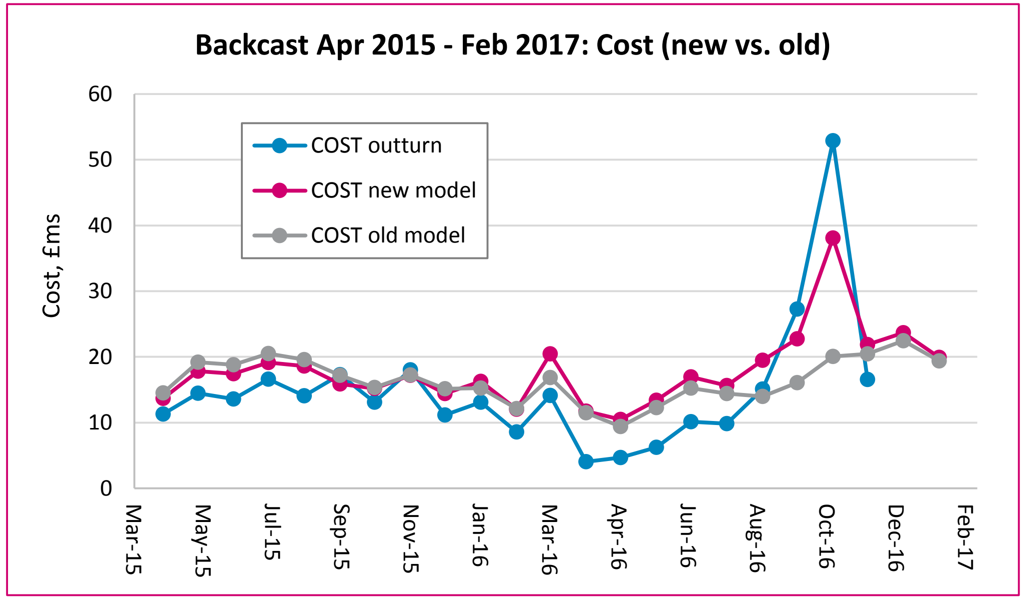
Assessment

- The refreshed coefficients for 2017-18 are used throughout this analysis of the new and the old models. No outturn values were available for VWA_OR_P for Jan 2017 and Feb 2017
- The overall performance of prediction is better on the monthly level than on the half hourly level.
- OR_V: the values are overestimated consistently.
- OR_P: the new model performs better than the old model, capturing partly the price peaks by using directly the ex-post OR_P_HH data in one branch (i.e. for half of the time).

Operating cost (monthly)

Operating Reserve Cost

Costs (in £m)	Outturn	New model	Old model
Apr 2015 – Mar 2016	165.48	198.16	201.76
Apr 2016 – Dec 2016	146.73	170.43	133.39



Overview of analysis

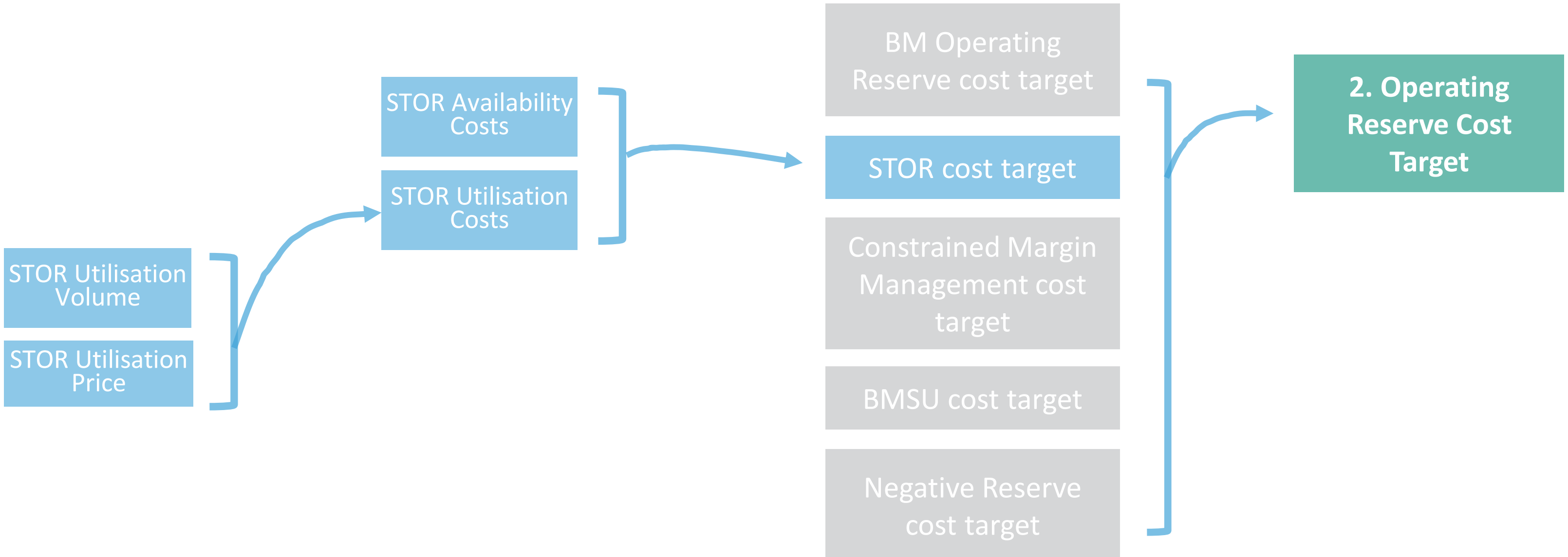
- This analysis looks at the cost and volume of Operating Reserve with the impact of Energy Reference Price and STOR Utilisation Costs stripped out. This is to highlight the performance of OR_V_HH and OR_P_HH models on a monthly level.
  - **OR_V** = msum(OR_V_HH)
  - **VWA_OR_P** = msum(OR_V_HH*OR_P_HH) / msum(OR_V_HH)
  - **COST** = OR_V*VWA_OR_P = msum(OR_V_HH*OR_P_HH)
  - **New Model** – refers to the new calculation of OR_P_HH (which has a combination of ex-post and modelled prices)
  - **Old model** – refers to the single regression model

Assessment

- Combining volumes and prices to consider costs on a monthly basis, the new model of OR_P_HH yields a slightly better prediction of the cost for Apr 2015 – Mar 2016, but a worse prediction for Apr-2016 – Dec-2016, mainly due to the overestimation in OR_V.
- No outturn values were available for OR_C for Jan 2017 and Feb 2017

STOR Cost Target

STOR_C



16/17 Target: £69.3m
16/17 Cost: £72.2m

Qualitative overview

- Short Term Operating Reserve (STOR) is reserve procured by the SO via a competitive tender process. STOR providers are paid availability fees (STOR_A_C) for making capacity available within defined periods, and Utilisation Payments when STOR is called upon (STOR_UC). These costs are modelled separately to calculate total STOR_C.
- The calculation for STOR_A_C reflects the monthly average forecast for available STOR (adjusted to remove long term STOR), the number of STOR hours in a month, and an ex-post STOR availability price (STOR_A_P) reflecting all STOR committed in that month.
- STOR Utilisation Costs are based on a volume (STOR_V) derived as a total percentage of total Operating Reserve Volume, adjusted for the amount of STOR contracted in a given month. The price component is made up of a weighted average of the utilisation prices of the most economic bids submitted as tenders.

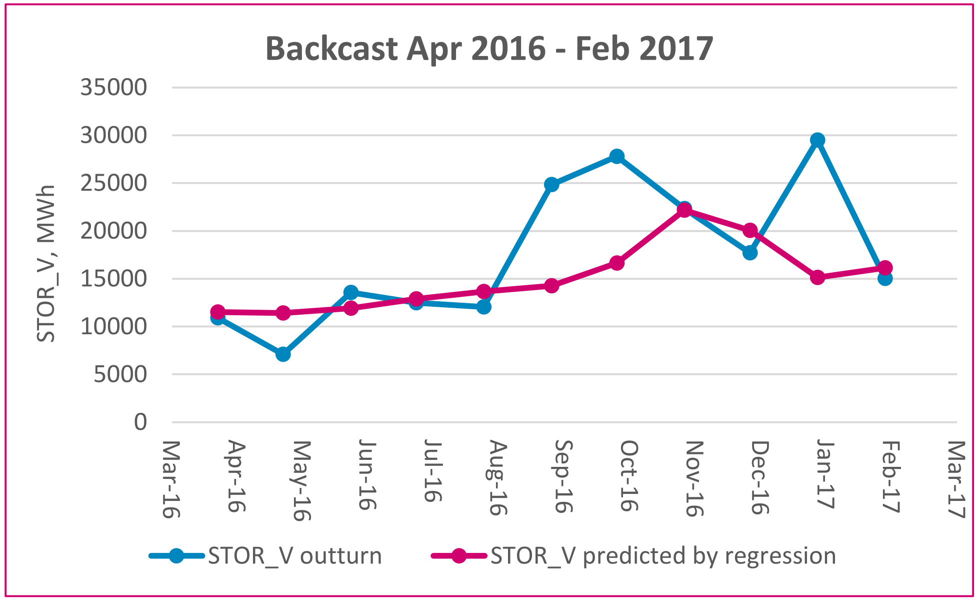
2017/18 changes

- Coefficients in the regression model were refreshed

STOR Utilisation Volume

STOR_V

Overall performance		**Adjusted R^2**
Overall fitting / prediction		0.81
Individual input performance		***p*-value**
C_0	Intercept (set to 0)	(N/A)
C_1	OR_V [i.e. msum(OR_V_HH)]	0.03
C_2	Avg_Available_STOR_V	~ 0

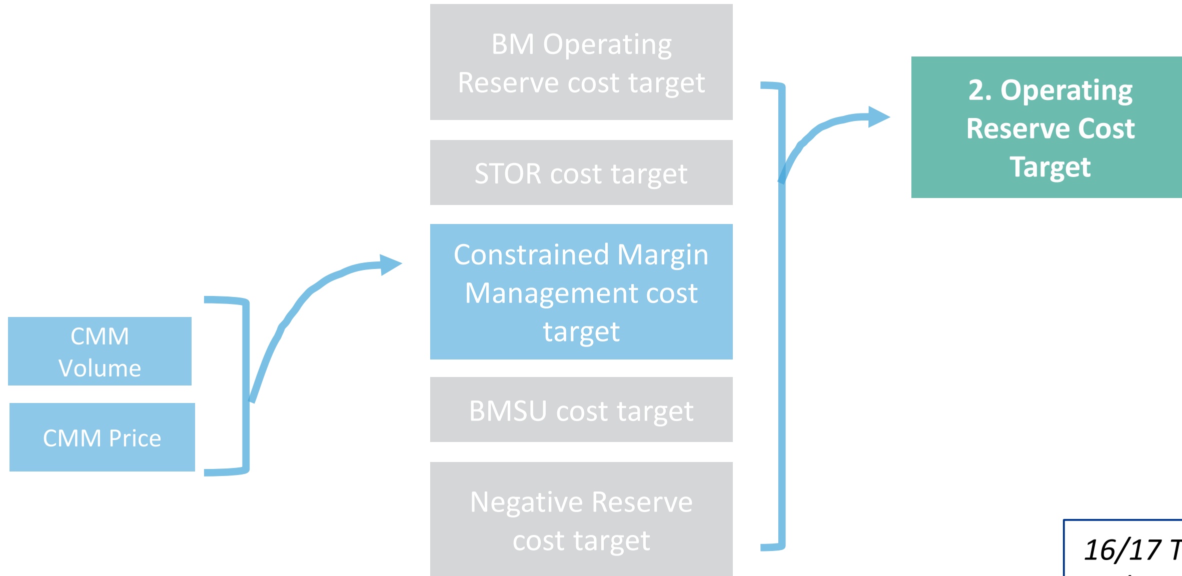


Assessment

- The monthly STOR utilisation volume target is the result of a linear model which uses the MW of STOR available and total Operating Reserve volume as variables. This estimates the percentage of the total Operating Reserve volume which was STOR utilisation, with an adjustment to reflect the amount of STOR contracted.
- The performance of this regression model for STOR_V would only affect the calculation of STOR_U_C; and not the total BM cost, since the total BM cost requires adding up OR_C and STOR_C, where the term of STOR_U_C is cancelled out.

CMM Cost

CMM_C



16/17 Target: £19.8m
*16/17 Cost: £43m**

Qualitative overview

- Constrained Margin Management (CMM) costs represent the costs of managing and replacing operating reserve that has been 'sterilised' behind a constraint boundary.
- The volume is forecast using a linear model that has an intercept term and using the volume of constraint bids forecast by PLEXOS.
- The price is set using a linear model that reflects an intercept term, the volume of CMM, and a volume weighted average of operating reserve price (VWA_Op_Reserve_P).

2017/18 changes

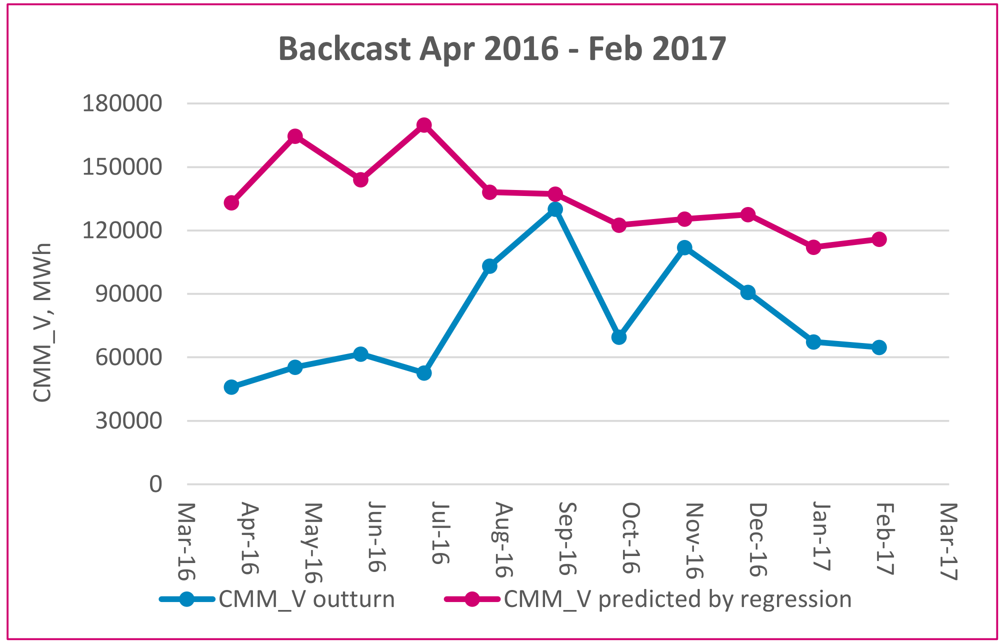
- Coefficients in the regression model were refreshed

Not including Forward Constrained Margin costs

CMM Volume

CMM_V

Overall performance		R^2
Overall fitting / prediction		0.081
Individual input performance		***p*-value**
C_0	Intercept	0.003
C_1	Constraint_Bid_V	0.018



Assessment

- Less satisfactory overall performance predicted using one input variable suggests that this input is not sufficient to fit and/or explain the variation of the output CMM_V.
- In particular the relative trend between Constraint_Bid_V and the output shifted completely around Jan-2016, switching from (a mostly) positive correlation to (majorly) negative correlation.
- As a result, the volume is overestimated consistently for the period of Apr 2016 – Feb 2017.

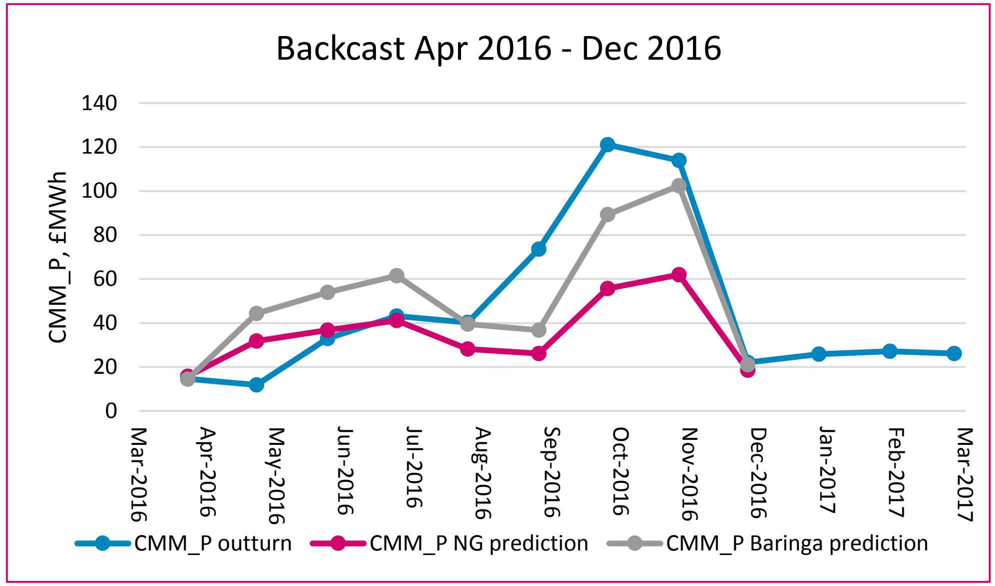
Outstanding clarifications / recommendations

- Researching whether and how the relative trend changes in 2017-18 between the input and the output would shed light on how predictive the input Constraint_Bid_V could be for the coming FY.
- Searching for more predictive input variables is worth considering in order to improve the performance of this regression model.

CMM Price

CMM_P

Overall performance		Adjusted R^2
Overall fitting / prediction		0.74
Individual input performance		***p*-value**
C_0	Intercept	0.86
C_1	CMM_V	0.12
C_2	VWA_Op_Reserve_P	~ 0



Challenges

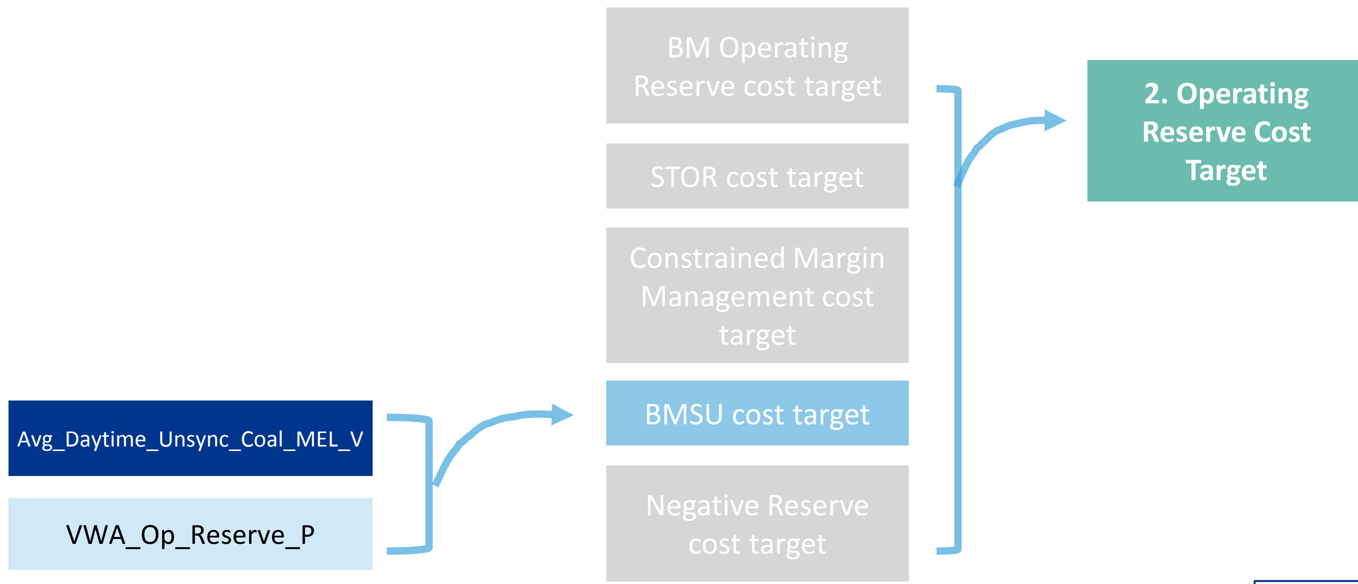
- A different set of coefficients was obtained when we tried to reproduce the coefficient refreshing process specified in the methodology documentation (v7).
- The adjusted R^2 and the *p*-values reported above are based on the coefficients we obtained.

Outstanding clarifications / recommendations

- NG has confirmed that a filter is applied to the "average monthly out of money price" before refreshing the coefficients. More specifically, a data point is retained if VWA_CMMorig_OOM_P_M_EP < £100/MWh.
- However, we are unable to reproduce the filtering and thus the coefficient refreshing process due to data availability (as of 31 May 2017). We have recommended revising the methodologies to outline the step of filtering. Please refer to Query #99 and #120 in Baringa BSIS Review Issues Log for more details.

Balancing Mechanism Start Up cost target

BMSU_C



16/17 Target: £4.4m
16/17 Cost: £6.5m

Qualitative overview

- The BM Start-up Service gives National Grid access to additional generating BMUs that could not be made available in BM timescales due to their technical characteristics and associated lead-times, and that would not otherwise have run. These costs include the costs of warming BMUs, or holding them ready to sync ('hot standby').
- The model for BMSU costs is a linear regression that uses an intercept, the volume of unsynchronised MEL at 6 hours ahead on coal fueled plant for daytime hours and the volume weighted average Operating Reserve price. The model essentially assumes a standard cost per month, a proportion of which is dependent on the Operating Reserve price. The unsynchronised MEL term is specifically the average of daytime values as this is the typical period during which BMSU actions would be taken.

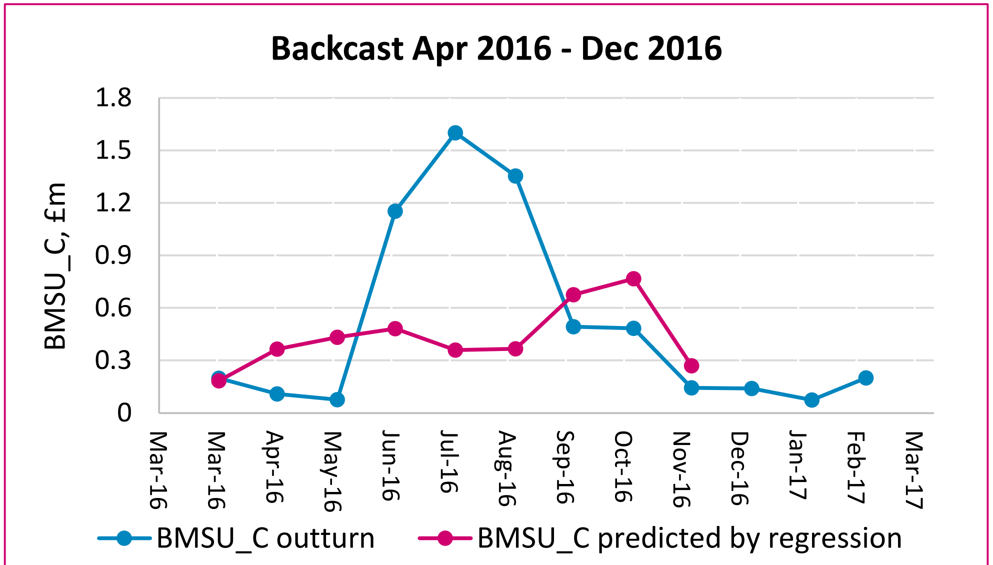
2017/18 changes

- The coefficients were refreshed

BM Start-Up Cost

BMSU_C

Overall performance		Adjusted R^2
Overall fitting / prediction		0.018
Individual input performance		***p*-value**
C_0	Intercept	0.77
C_1	Avg_Daytime_Unsync_Coal_MEL_V	0.24
C_2	VWA_Op_Reserve_P	0.12



Assessment

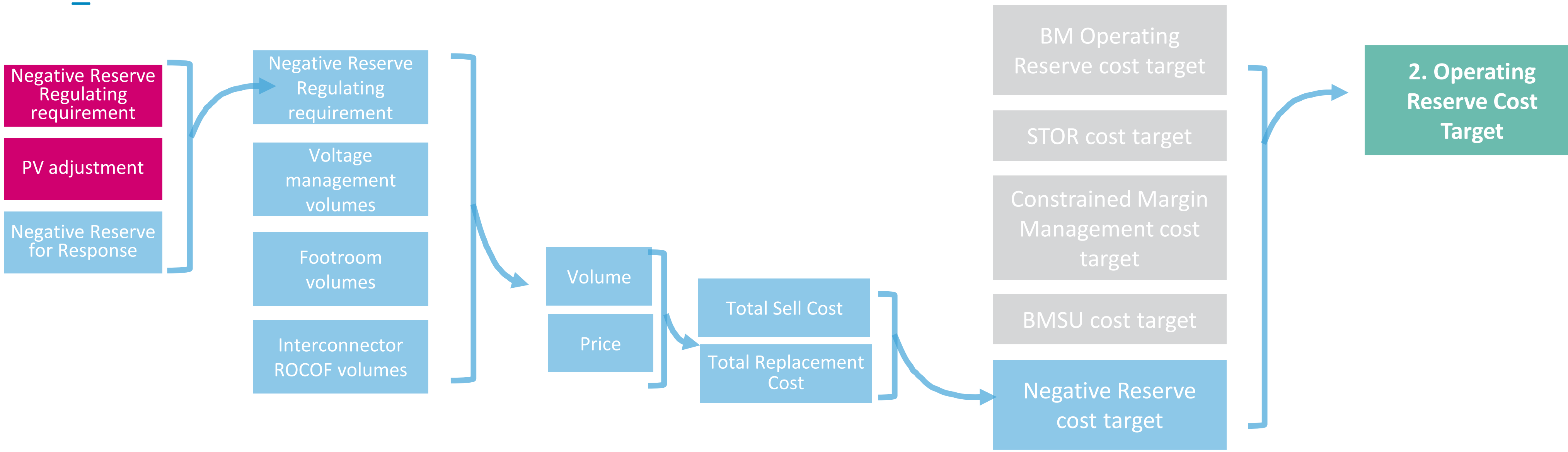
- Less satisfactory overall performance combined with insignificant input variables suggests that the inputs currently in use are unable to capture and/or explain the variation of the output BMSU_C.
- Judging from the relative trend between the inputs and the output, fitting is particularly challenging for the past FY (particularly from Apr 2016 onwards), because (a) Avg_Daytime_Unsyc_Coal_MEL_V (X_1) did not capture the peak in BMSU_C as it used to, and (b) VWA_Op_Reserve_P (X_2) experienced a significant change in trend in the same period.
- As a result, the total BMSU cost is underestimated for the period of Apr 2016 – Dec 2016.

Outstanding clarifications / recommendations

- Researching whether and how the relative trend changes in 2017-18 between the inputs and the output would shed light on how predictive the inputs could be for the coming FY.
- Replacing the current input variables by more predictive ones is worth considering in order to improve the performance of this regression model.

Negative Reserve Costs

NR_C



16/17 Target: £19.1m
16/17 Cost: £24.3m

Qualitative overview

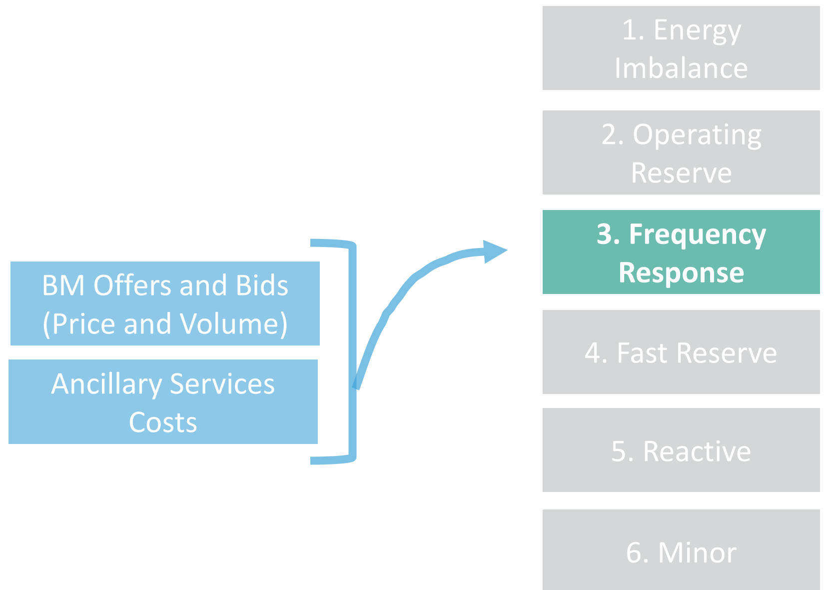
- Negative reserve (also know as downward regulation or footroom) refers to the SO's capability to reduce generation output. When demand is low and the majority of generation is operating inflexibly at/near its minimum stable output, the SO can desync some BMUs (CCGTs, coal, oil and pumped storage), and change French and Dutch interconnector flows through trades.
- Negative Reserve Volume is calculated based on a deterministic model. It is calculated using the underlying total requirement, the amount of negative reserve delivered by the market through available capacity, and market length (i.e. NIV), as well as adjustments for modelled RoCoF interconnector trades and modelled voltage actions.

2017/18 changes

- A new deterministic model was introduced for negative reserve, replacing a linear regression model.

Frequency Response

FRR_C



16/17 Target: £183m
16/17 Cost: £145.2m

Qualitative overview

- The SO can procure a number of different kinds of balancing service to manage second-by-second changes on the system, and keep the system frequency within the statutory limits set out in the NETS SQSS.
- The volume of response required is set to ensure that frequency is kept within statutory limits if a significant event occurs, such as the loss of the largest infeed
- FRR_C comprises costs of positioning BM units to provide response (bids and offers in the BM), and the ancillary service fees which include the response energy payment and holding fees for the provision of response services.

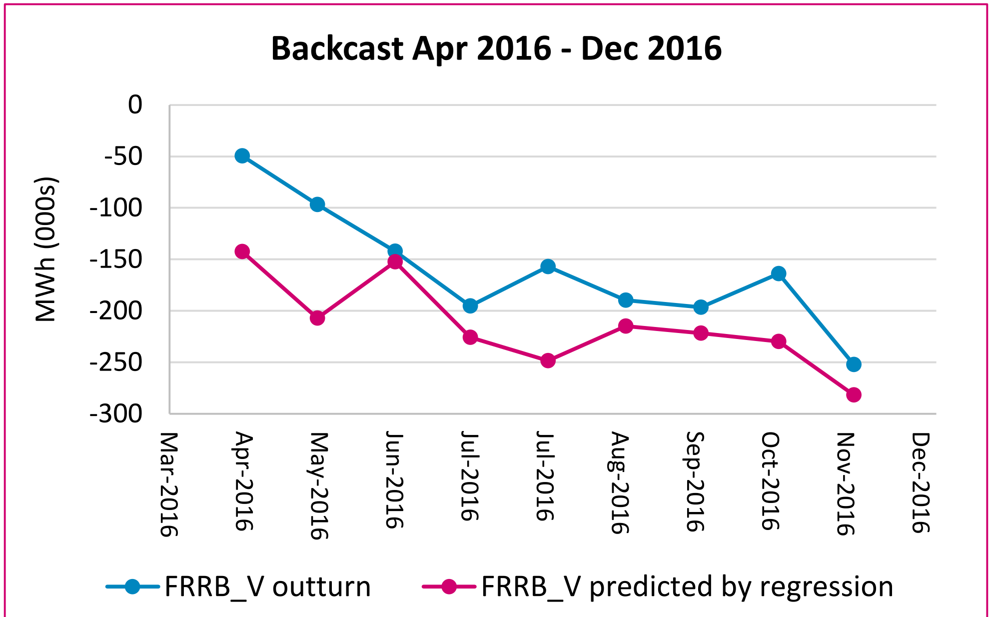
2017/18 changes

- The coefficients were refreshed

Frequency Response – Bid Volume

FRRB_V

Overall performance		**Adjusted R^2**
Overall fitting / prediction		0.28
Individual input performance		***p*-value**
C_0	Intercept	0.30
C_1	Avg_NI_V	~ 0
C_2	Avg_Headroom_V	0.40
C_3	Avg_Available_Contracted_Firm_Static_V	0.12
C_4	OR_V [i.e. msum(OR_V_HH)]	~ 0



Assessment

- Less satisfactory overall performance combined with some significant inputs suggests that the current inputs are not sufficient to fit and/or explain the variation of the output FRRB_V.
- As a result, the volume (the absolute value) is overestimated consistently for the period of Apr 2016 – Dec 2016.

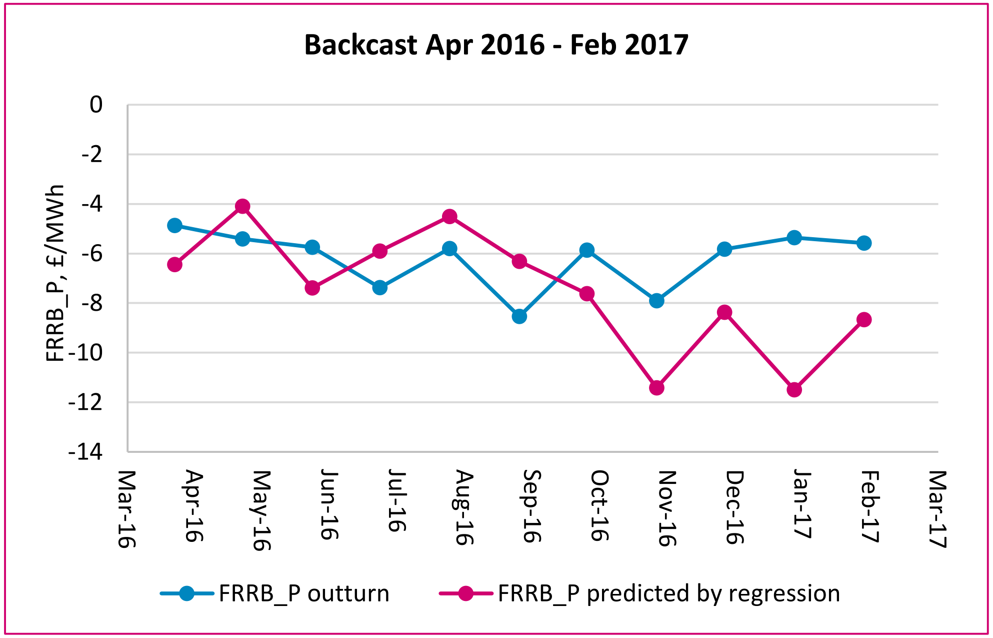
Outstanding clarifications / recommendations

- Searching for more predictive input variables is necessary in order to improve the performance of this regression model.

Frequency Response – Bid Price

FRRB_P

Overall performance		Adjusted R^2
Overall fitting / prediction		0.88
Individual input performance		***p*-value**
C_0	Intercept (set to 0)	(N/A)
C_1	Avg_NI_V	0.007
C_2	Avg_ER_P	0.068
C_3	Avg_Marginal_Fuel_P	0.720



Assessment

- Satisfactory overall performance combined with significant inputs suggests that this regression model is working well.
- The price (the absolute value) is overestimated between Nov 2016 and Feb 2016. Together with the overestimated FRRB_V, the Frequency Response Bid Cost would be overestimated for this period.
- There exists very strong collinearity between Avg_ER_P (X_2) and Avg_Marginal_Fuel_P (X_3) for the entire period of Apr 2011 – Feb 2017. This phenomenon does not affect the predictive power of this specific model, although it may reduce the stability.

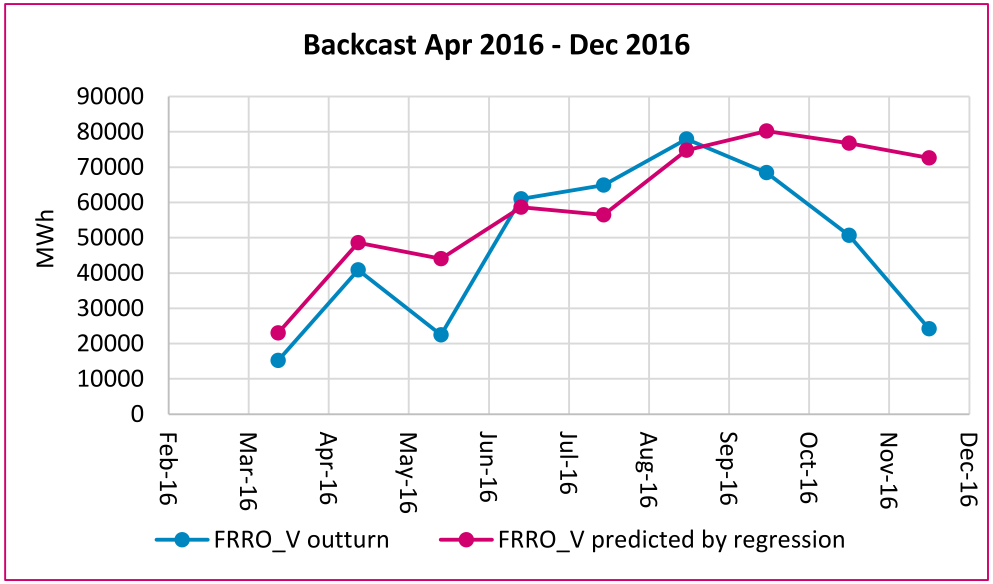
Outstanding clarifications / recommendations

- The marginal fuel price metric was based on coal rather than gas for over 95% of 2016/17, but with recent plant closures, the capacity of coal plant to provide response/reserve services is much more limited. Going forward, it should be considered whether the reference to coal generation costs is still appropriate.

Frequency Response – Offer Volume

FRRO_V

Overall performance		Adjusted R^2
Overall fitting / prediction		0.46
Individual input performance		***p*-value**
C_0	Intercept	0.058
C_1	Demand_V	0.014
C_2	Avg_Overnight_Footroom_V	~ 0
C_3	Avg_Overnight_Wind_Volatility_V	0.004
C_4	Avg_Overnight_IC_Flow_V	~ 0
C_5	Avg_Overnight_NI_V	0.337



Assessment

- Moderate overall performance combined with significant inputs suggests that the current inputs fit and/or explain partly the variation of the output FRRO_V and that there is some room for improvement.
- The fitting is better after Jan 2013 than before Jan 2013 (see appendix), which means that the backcast for Apr 2016 – Dec 2016 is in fact more accurate than the adjusted R2 has suggested.
- Meanwhile, the deviation (towards over-estimation) for Nov 2016 and Dec 2016 may indicate a future trend shift.

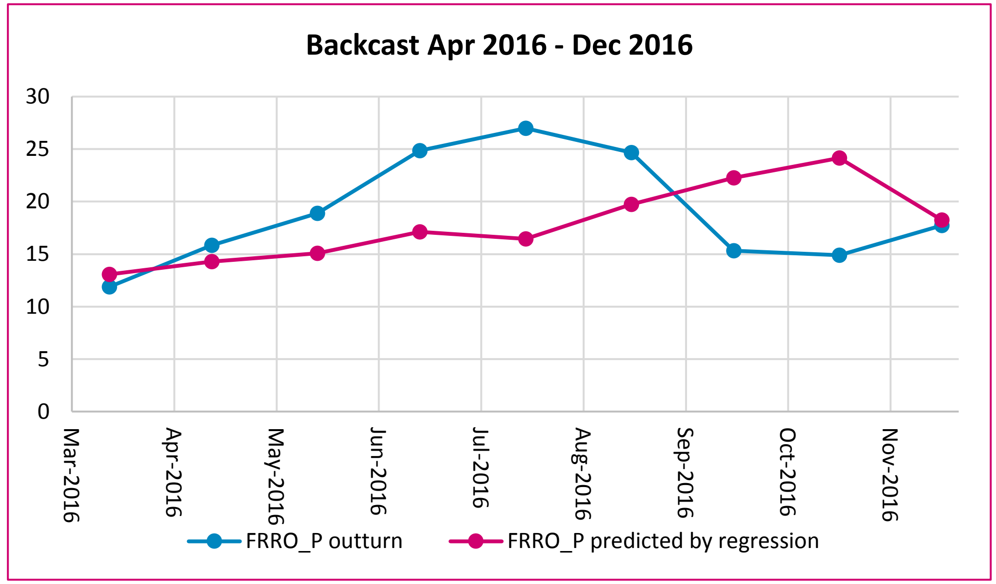
Outstanding clarifications / recommendations

- Monitoring whether and how the predicted FRRO_V (when the ex-post data are available at the end of a month) continues to deviate from the real values in 2017-18 would shed light on whether the trend shifts plus whether and how the model needs to respond to the shift.

Frequency Response – Offer Price

FRRO_P

Overall performance		**Adjusted R^2**
Overall fitting / prediction		0.91
Individual input performance		***p*-value**
C_0	Intercept (set to 0)	(N/A)
C_1	FRRO_V	0.018
C_2	Avg_SPNIRP_P	~ 0



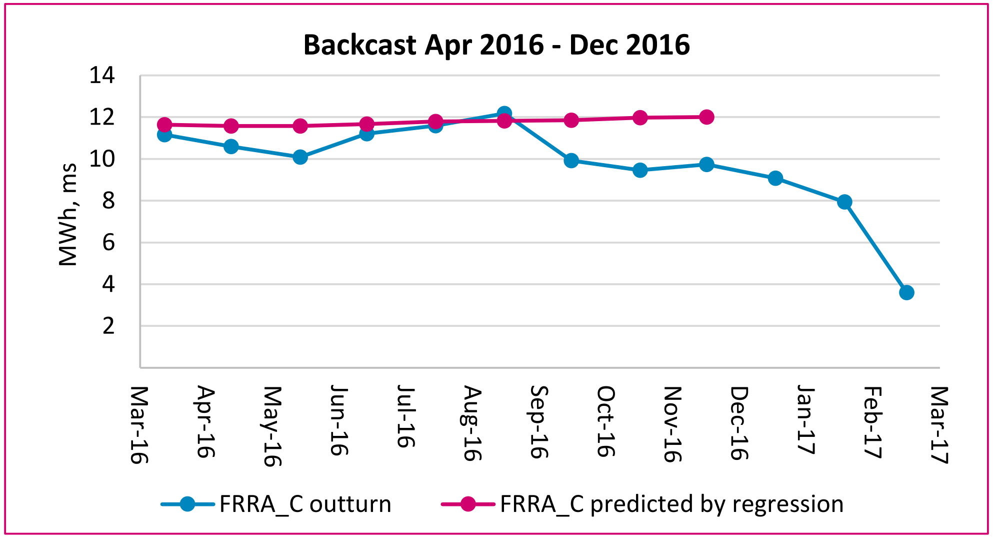
Assessment

- Satisfactory overall performance combined with significant inputs suggests that this regression model is working well in general. Please note that the high adjusted R^2 value of 0.91 characterises the performance over a longer period (Apr 2011 – Dec 2016) than the most recent period displayed here (Apr 2016 – Dec 2016).
- For Apr 2016 – Dec 2016, the Offer Price is slightly underestimated on average, which would balance out the slightly overestimated Offer Volume for the same period and give a relatively accurate estimate for the Frequency Response Offer Cost.

Frequency Response – Ancillary Services Cost

FRRA_C

Overall performance		Adjusted R^2
Overall fitting / prediction		0.97
Individual input performance		***p*-value**
C_0	Intercept (set to 0)	(N/A)
C_1	Avg_Available_Contracted_Firm_Static	0.18
C_2	Avg_Available_Contracted_Firm_Dynamic	0.83
C_3	Avg_Marginal_Fuel_P	0.66
C_4	Retail Price Index (RPI)	~ 0



Assessment

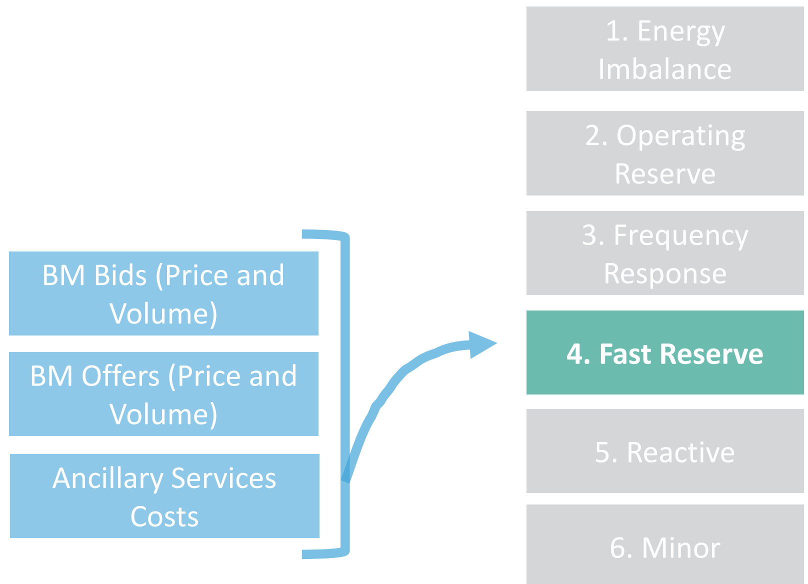
- The overall satisfactory performance was largely driven by RPI (X_4). This suggests that the resultant relatively flat predicted FRRA_C values give good estimation for the period of Apr 2011 – Dec 2016.
- However, a massive drop is observed for Dec 2016 – Mar 2017, where these real FRRA_C values are not included in the model training / coefficient refreshing, whereas the coefficients derived from the data of Apr 2011 – Dec 2016 will continue to predict the cost to remain at the same level and therefore will fail to capture the drop, hence overestimating the cost.

Outstanding clarifications / recommendations

- Monitoring whether and how the real FRRA_C continues to deviate from the relatively flat prediction in 2017-18 would shed light on whether the trend shifts plus whether and how to adjust the model to respond to the shift.
- In some cases, searching for more predictive input variables would be necessary in order to improve the performance of this regression model for the period of Dec 2016 onwards.

Fast Reserve

FR_C



16/17 Target: £152.9m
16/17 Cost: £93.6m

Qualitative overview

- Fast Reserve is a balancing service that is used to control frequency changes that might arise from sudden changes in generation or demand. It is provided by balancing services that can deliver active power following an electronic dispatch instruction rom the SO.
- FR_C comprises costs of positioning BM units and the ancillary service costs associated with first Fast Reserve contracts, or any optional service fees.
- The fast reserve bid volume (FRB_V) is calculated as a static value, with prices set by the average ER_P. The Fast Reserve Offer Volumes (FRB_V) are predicted using a linear regression on generation volatility, with prices set using the average ER_P and the average Marginal_Fuel_P.
- FRA_C are calculated using a linear model, reflecting wind volatility and RPI.

2017/18 changes

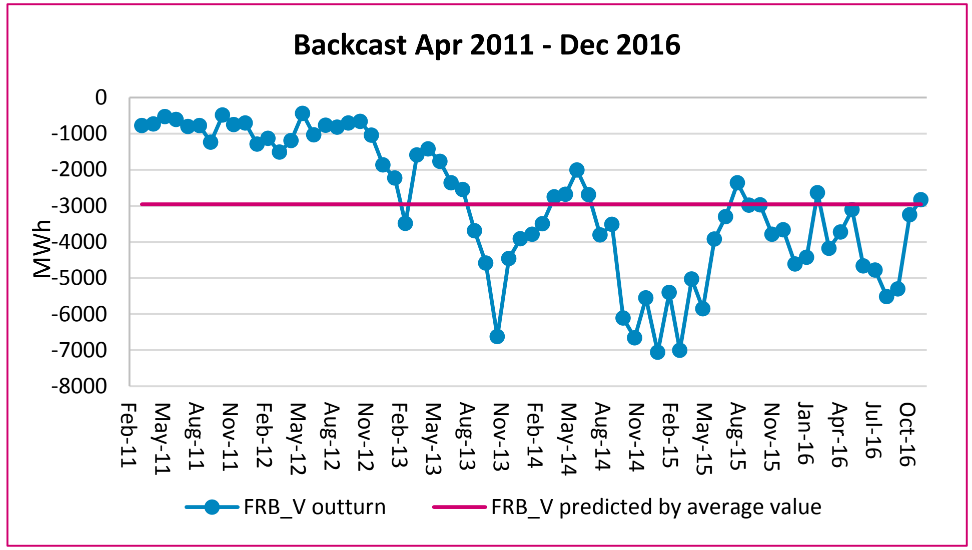
- Regression coefficients were refreshed.

Fast Reserve – Bid Volume

FRB_V

Model description

- For FY 2017-18, FRB_V is modelled as a fixed value equal to the average of the outturn FRB_V over the period of Apr 2011 – Dec 2016, which is calculated to be -2959.55 MWh.
- The fixed value used for predicting FRB_V was recalculated and changed for 2017/18



Assessment

- Although the methodology documentation states that bid volumes have been "fairly stable across history", the outturn FRB_V experiences considerable fluctuation over the period of Apr 2011 – Dec 2016. This observation suggests that a fixed average value is not sufficient to capture the variation of FRB_V.
- In addition, the annual average also shifts over the years, from approx. -1000 MWh in 2011-12 to approx. -4000 MWh in 2016-17. Therefore, averaging over 6 years may not give a representative value.
- As a result, the volume (the absolute value) is underestimated consistently for the period of Apr 2016 – Dec 2016.

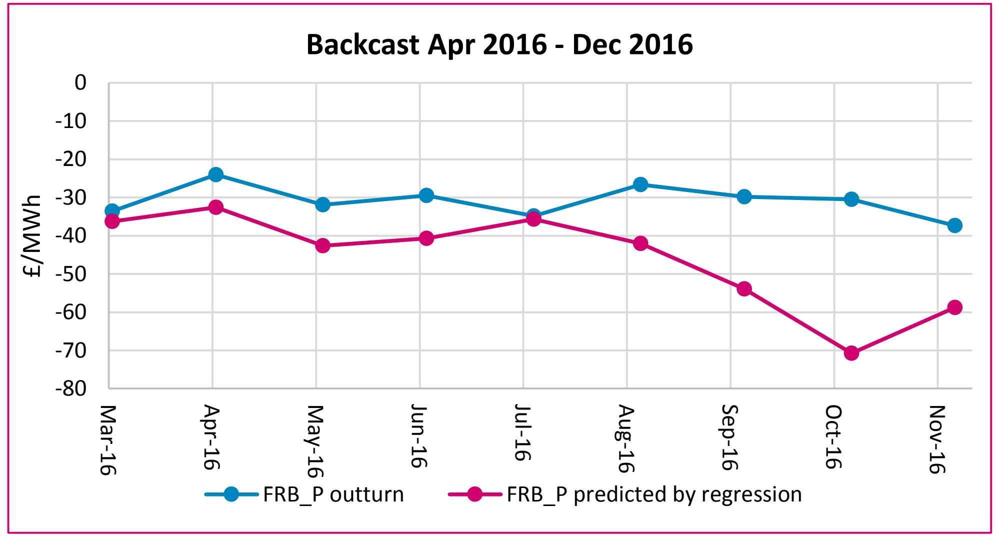
Outstanding clarifications / recommendations

- Averaging over a shorter period of time or replacing the average value by a linear regression model is worth considering in order to improve the accuracy of the prediction.

Fast Reserve – Bid Price

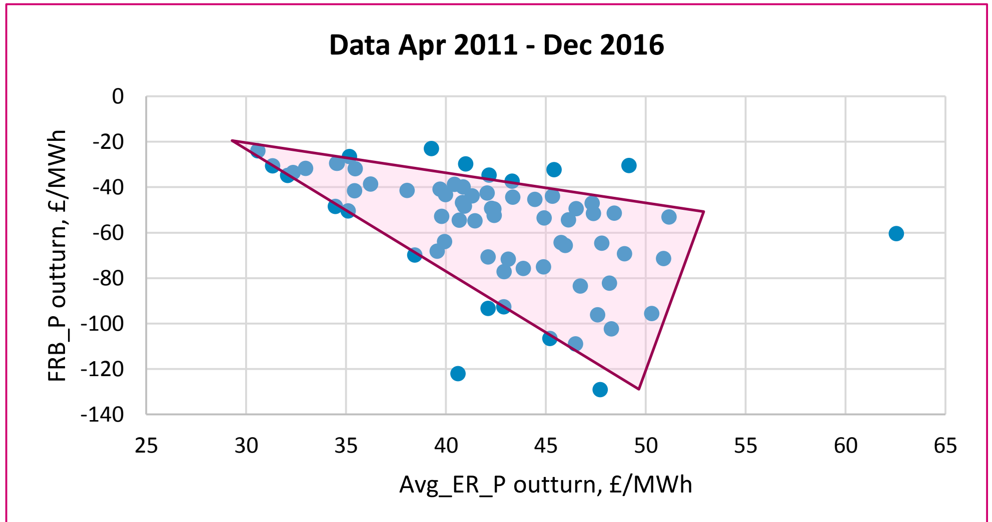
FRB_P

Overall performance	R^2
Overall fitting / prediction	0.23
Individual input performance	***p*-value**
C_0 Intercept	0.13
C_1 AVG_ER_P	~ 0



Assessment

- Less satisfactory overall performance predicted using one input variable suggests that this input alone is not sufficient to fit and/or explain the variation of the output FRB_P. The output FRB_P spreads more widely than a linear regression model can capture (as illustrated by the pink triangle on the bottom right graph). For example, when the input AVG_ER_P is approx. 48 £/MWh, the output FRB_P may range from -45 to -130 £/MWh.
- The price (the absolute value) is overestimated consistently for the period of Apr 2016 – Dec 2016.



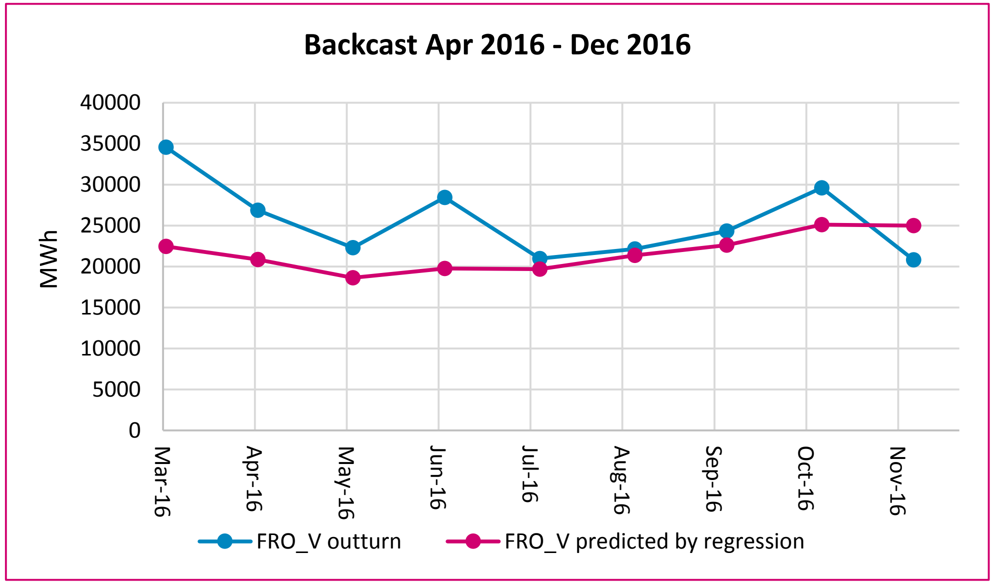
Outstanding clarifications / recommendations

- Searching for more predictive input variables is necessary in order to improve the performance of this regression model.

Fast Reserve – Offer Volume

FRO_V

Overall performance		Adjusted R^2
Overall fitting / prediction		0.94
Individual input performance		***p*-value**
C_0	Intercept (set to 0)	(N/A)
C_1	IC_Flow_Volatility_V	0.086
C_2	Wind_Volatility_V	~ 0
C_3	Demand_Volatility_V	~ 0
C_4	Is_Summer	0.512



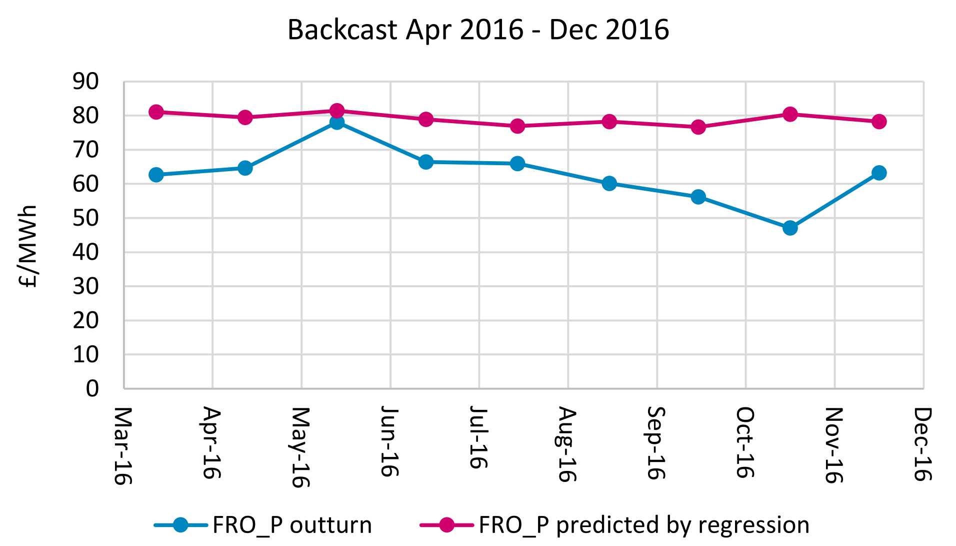
Assessment

- Satisfactory overall performance combined with significant inputs suggests that this regression model is working well in general.
- More specifically down to the most recent period of Apr 2016 – Dec 2016, FRO_V is underestimated slightly but consistently. It should be more or less balanced out by the slightly overestimated FRO_P over the same period, and therefore the predicted Fast Reserve Offer Cost would be relatively accurate.

Fast Reserve – Offer Price

FRO_P

Overall performance	Adjusted R^2
Overall fitting / prediction	0.0045
Individual input performance	***p*-value**
C_0 Intercept	~ 0
C_1 Avg_ER_P	0.23
C_2 Avg_Marginal_Fuel_P	0.14



Assessment

- Unsatisfactory overall performance combined with insignificant input variables and a significant intercept suggests that the inputs currently in use are unable to capture and/or explain the variation of the output FRO_P and that the prediction is dominantly made by the intercept (i.e. a fixed value), suggesting there is not much predictive power in this regression model.
- One factor affecting the predictive power is the very strong collinearity between Avg_ER_P (X_1) and Avg_Marginal_Fuel_P (X_2) for the entire period of Apr 2011 – Dec 2016. More specifically, the only two input variables of this model are almost equal in value. Given that their coefficients almost cancel out each other (C_1 = 0.61 and C_2 = -0.74), the prediction has to rely dominantly on the intercept and therefore becomes flat.
- FRO_P turns out overestimated consistently for the period of Apr 2016 – Dec 2016. It should be more or less balanced out by the slightly underestimated FRO_V over the same period, and therefore the predicted Fast Reserve Offer Cost would be relatively accurate.

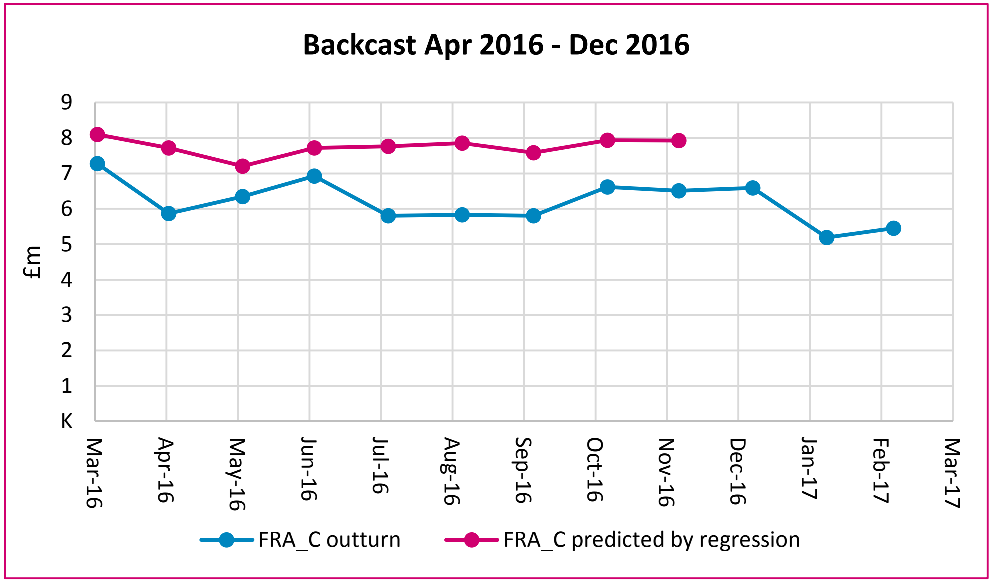
Outstanding clarifications / recommendations

- Searching for more predictive input variables would be necessary in order to improve the performance of this regression model.
- The marginal fuel price metric was based on coal rather than gas for over 95% of 2016/17, but with recent plant closures, the capacity of coal plant to provide response/reserve services is much more limited. Going forward, it should be considered whether the reference to coal generation costs is still appropriate.
- Monitoring whether and how the real FRO_P develops in 2017-18 in relation to the relatively flat prediction would shed light on whether the trend shifts.

Fast Reserve – Ancillary Services Cost

FRA_C

Overall performance		Adjusted R^2
Overall fitting / prediction		0.065
Individual input performance		***p*-value**
C_0	Intercept	0.040
C_1	Wind_Volatility_V	0.031
C_2	RPI	0.267



Assessment

- Less satisfactory overall performance combined with one significant input variable suggests that the inputs currently in use are unable to capture and/or explain the variation of the output FRA_C.
- More specifically, the trend of the output variable changes around early to mid 2014, from increasing over time to decreasing over time. However, the trend of both input variables remains unchanged, still increasing over time, and therefore a less satisfactory fitting is yielded.
- FRA_C turns out overestimated consistently for the period of Apr 2016 – Dec 2016.

Outstanding clarifications / recommendations

- Searching for more predictive input variables would be necessary in order to improve the performance of this regression model.
- Researching whether and how the relative trend changes in 2017-18 between the inputs and the output would shed light on how predictive the inputs could be for the coming FY.

Reactive Power Costs

REAC_C

1. Energy Imbalance

2. Operating Reserve

3. Frequency Response

4. Fast Reserve

5. Reactive

6. Minor

Reactive Power Volume

Reactive Power Default Price

16/17 Target: £88.8m
16/17 Cost: £86.1m

Qualitative overview

- Reactive power flows determine voltage on the system, and the SO must ensure that there are sufficient Reactive Power reserves on a local basis. The SO procures Reactive Power as a balancing service and pays providers a price set out in the CUSC.
- The Reactive Power model derives Reactive Power cost (in £) from a forecast of reactive demand (in MVArh) and an assumed price of Reactive Power.

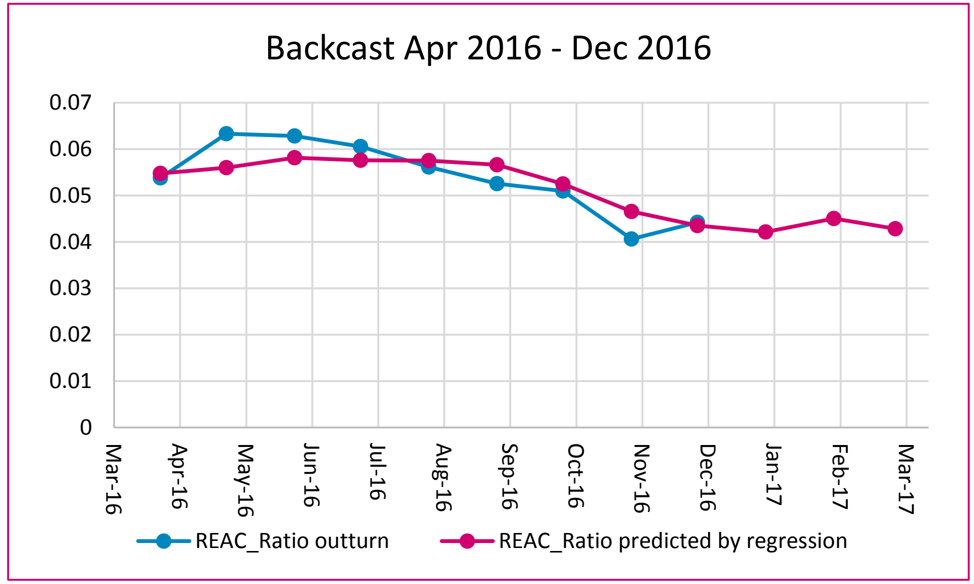
2017/18 changes

- The Reactive Demand Ratio coefficients were refreshed

Reactive Demand Ratio

REAC_Ratio

Overall performance		Adjusted R^2
Overall fitting / prediction		0.86
Individual input performance		***p*-value**
C_0	Intercept	~ 0
C_1	Month_ID	~ 0
C_2	Demand_V	~ 0
C_3	Is_Winter	0.019
C_4	Is_BST	0.002

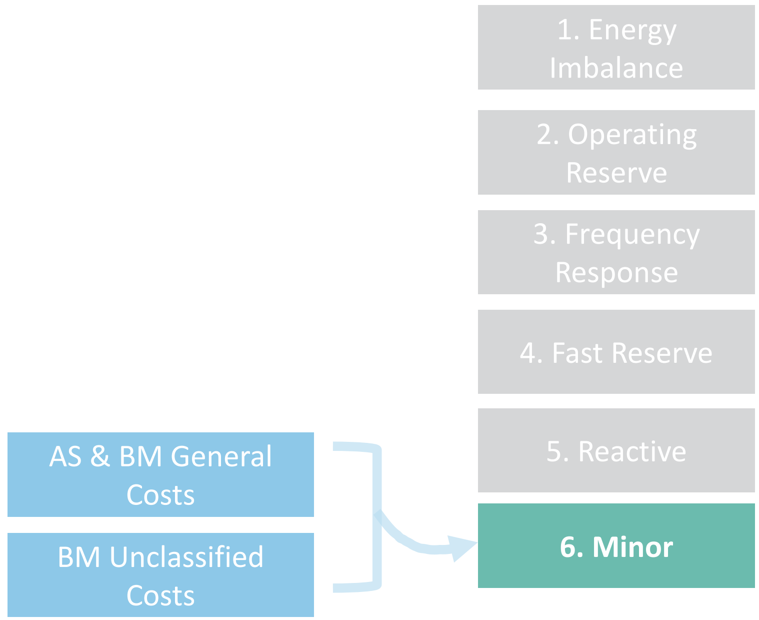


Assessment

- Satisfactory overall performance combined with significant inputs suggests that this regression model is working well.

Minor Costs

AS_BM_C and UN_BM_C



Qualitative overview

- The minor cost category is made up of two components, AS & BM General costs (AS_BM_C) and BM Unclassified costs (UN_BM_C).
- AS & BM General Costs are incurred from operating the system which do not directly correlate to other categories – e.g. Non-Delivery charges, unwinding SO actions, SO-SO actions invoked by other SOs, trading fees and bank charges. BM Unclassified Costs include costs which do not meet any of the other categories – e.g. synchronising individual GTs on already synchronised CCGT, or untagged constraint actions which do not meet any of the criteria for the other categories.
- Both costs are modelled as a fixed percentage / ratio of the total BM costs. The ratios are derived from historical data using a deterministic approach, and they are multiplied by the total BM target cost to give the corresponding minor costs for the month.

2017/18 changes

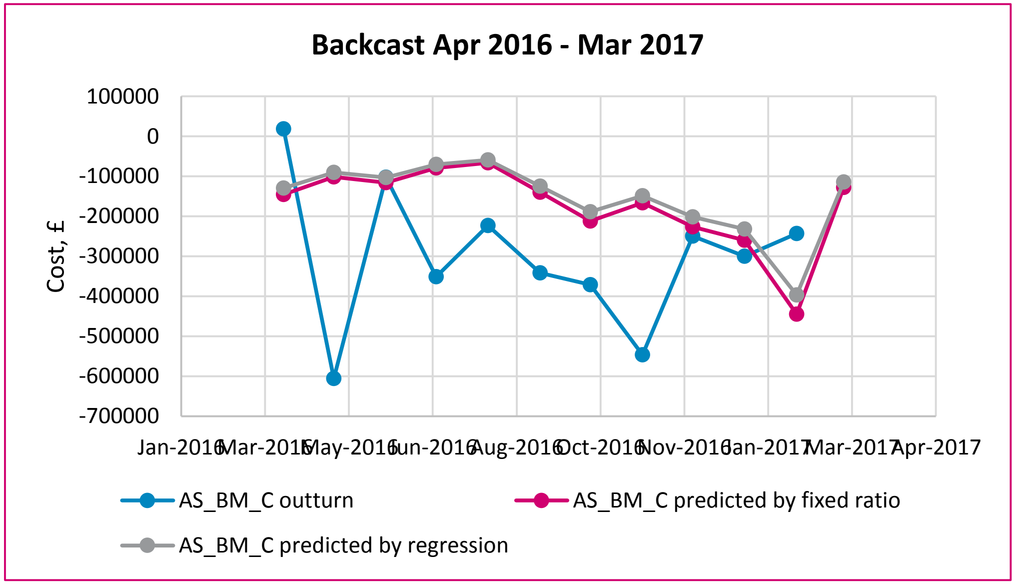
- The fixed ratios used for modelling AS_BM_C and UN_BM_C were refreshed.

Ancillary Services & Balancing Mechanism General Cost

AS_BM_C

Model description

- For FY 2017-18, AS_BM_C is modelled as the product of the outturn total BM cost TOT_BM_C and a fixed ratio, whose value is defined to be the quotient of the average outturn AS_BM_C over the period of Apr 2011 – Dec 2016 divided by the average outturn TOT_BM_C over the same period.
- This fixed ratio is recalculated and fixed to be **-0.00627801** for 2017-18.



Assessment

- In this specific case, prediction by linear regression gives almost identical results to prediction by fixed ratio. Therefore, the R^2 of the regression (0.33) can be viewed as a good indicator of the quality of the prediction made by the fixed ratio.
- The less satisfactory overall performance obtained using one fixed ratio suggests that this fixed ratio alone is not sufficient to capture and/or explain the variation of the output AS_BM_C. For example, when the input TOT_BM_C is approx. £27m, the output AS_BM_C may range from -£500k to £200k, i.e. the associated ratio ranges from -0.0185 to 0.00741.
- This is partly because there is a trend shift at around Oct 2014: the cost fluctuates around £0 before this point but around -£300k afterwards.
- As a result of averaging over the two periods together, AS_BM_C is overestimated (i.e. the income is underestimated) consistently for the period of Apr 2016 – Dec 2016.

Outstanding clarifications / recommendations

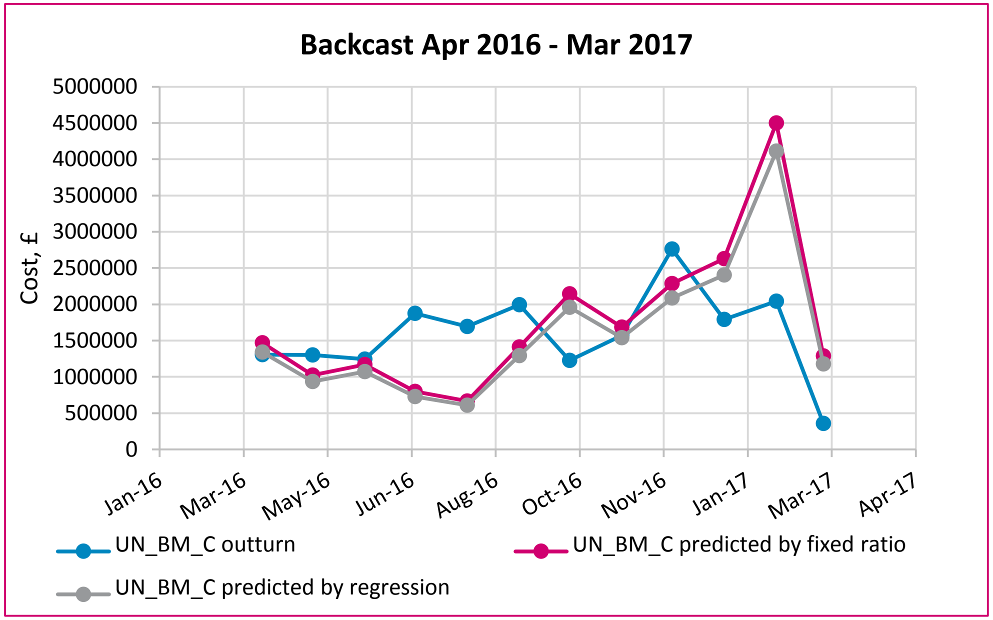
- Monitoring how the output AS_BM_C develops in 2017-18 would shed light on whether and how its trend shifts and how predictive the ratio between AS_BM_C and TOT_BM_C could be for the coming FY.
- Averaging over a shorter period of time or using linear regression instead is worth considering in order to improve the accuracy of prediction, especially in the case that the model itself would remain unchanged (i.e. still predicting using TOT_BM_C only).

Balancing Mechanism Unclassified Cost

UN_BM_C

Model description

- For FY 2017-18, UN_BM_C is modelled as the product of the outturn total BM cost TOT_BM_C and a fixed ratio, whose value is defined to be the quotient of the average outturn UN_BM_C over the period of Apr 2011 – Dec 2016 divided by the average outturn TOT_BM_C over the same period.
- This fixed ratio is recalculated and fixed to be **0.063477** for 2017-18.



Assessment

- In this specific case, prediction by linear regression gives almost identical results to prediction by fixed ratio. Therefore, the R^2 of the regression (0.83) can be viewed as a good indicator of the quality of the prediction made by the fixed ratio.
- The satisfactory overall performance predicted using one fixed ratio suggests that this fixed ratio is working well with the data that are used to determine it (Apr 2011 – Dec 2016).
- However, all 3 data points that are not used to determine the ratio (UN_BM_C of Jan 2017 – Mar 2017) turn out overestimated. Looking backward, this is fine because they balance out more or less the underestimation in the earlier months of the same FY; looking forward, nevertheless, it may indicate a future shift in the trend.

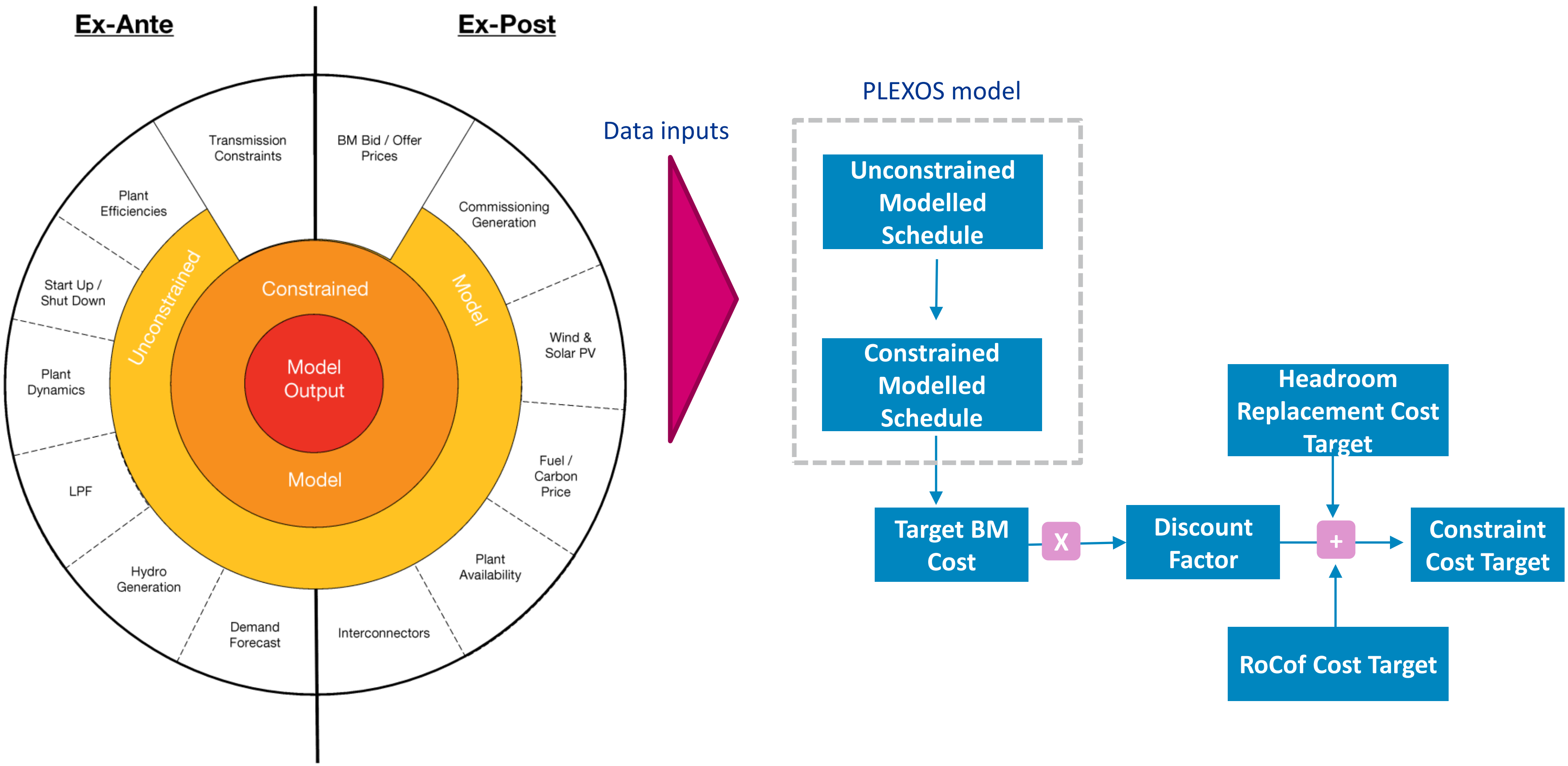
Outstanding clarifications / recommendations

- Monitoring how UN_BM_C develops in 2017-18 would shed light on whether and how its trend shifts and how predictive the ratio between UN_BM_C and TOT_BM_C could be for the coming FY.

Constraints model

Overview of model

The constraints model uses a PLEXOS-based representation of generation plant and the transmission network to simulate the costs of resolving grid constraints in the BM, starting from an unconstrained generation schedule



Key findings and recommendations

Dispatch of gas- and coal-fired power stations

Dispatch of gas- and coal-fired power stations

- Based on results from the backcast 2016/17 unconstrained PLEXOS run, the model appears to overstate gas-fired generation at the expense of coal-fired generation compared to the actual Final Physical Notifications (FPNs) submitted by these generators over the same period of time
- Note however that generator FPNs may reflect constraint management actions that National Grid has taken pre-Gate Closure (whereas the PLEXOS model assumes that constraint management is left to the BM)
- Furthermore we believe that the overall impact on constraint costs is likely to be limited for three reasons:
  - Firstly, the bid-offer spreads for coal/gas plant are not very significant – meaning that if, due to transmission bottlenecks, PLEXOS needs to ‘constrain down’ a gas plant in order to ‘constrain up’ a coal plant, this action would typically not incur significant costs
  - Secondly, the affected power stations are not located in Scotland where transmission constraints are encountered more often compared to England and Wales, and are typically more expensive to resolve due to significant wind penetration
  - Thirdly, this issue will become less relevant going forward as the share of coal-fired generation in the GB generation mix is further reduced

Key findings and recommendations

Constrained wind volumes

Constrained wind volumes

- Constrained wind volumes in the backcast 2016/17 PLEXOS run are higher compared to historical total bid volumes for GB wind plant over the same period
- For the period 1st April 2016 to 28th February 2017, for example, the total bid volume for GB wind plant equals 0.93 TWh of which we estimate that approximately 0.89 TWh were due to System balancing actions. This compares against constrained wind volumes of 1.58 TWh in the PLEXOS model
- From our discussions with National Grid we understand that the backcast 2016/17 PLEXOS model uses Year Ahead boundary limits which may differ significantly compared to outturn boundary limits
- Moreover, the PLEXOS model resolves all system congestion by simulated BM actions. In reality, a prudent SO may take additional measures to minimise constraint costs such as:
    - Temporary moving outages to optimise the plan, e.g. by recalling outages when windy weather is forecast in order to allow for less restrictive boundary limits
    - Similarly, enhanced ratings may temporarily be agreed with TO (again in order to reduce restriction of flows)
    - Trades with wind (for the period 2016/17, for example, 0.2 TWh of wind was constrained via trades)
    - Use of intertrips

Key findings and recommendations

Transmission boundary limits, demand data, and Western HVDC Link

Transmission boundary limits and demand data

- On balance we believe that a move to 8 week ahead transmission boundary limits (replacing year ahead limits) and 7 day ahead demand data (rather than year ahead) is a sensible one and should increase the accuracy of the model by using data closer to real time
- However, given that the related historical time series were not available to us, we were unable to quantify the expected reduction in forecast errors, and thus also the resultant improvement in model accuracy
- As a result, we are unable to comment on the expected impact of these changes to the 2017/18 network constraints costs set by the model, or their impact on the applicable discount factor

Western HVDC Link

- Until the Western HVDC link is fully commissioned, it will not be available for operational purposes.
- National Grid's proposed approach is that boundary flow limits assessed at 8 weeks ahead of scheduled commissioned date will have transfer capability assessed with both the Western HVDC Link available and unavailable, for the relevant boundaries affected. The ex post selection of the appropriate limit will then be built into the monthly process to best reflect system operation and the HVDC Link's commissioning status.
- We are satisfied that the proposed approach would not create an inherent bias when establishing network constraint targets and we believe it is fit for purpose for future use

Key findings and recommendations

Intertrips and discount factor

Intertrips and discount factor

- Intertrips are not modelled explicitly but National Grid recognises that intertrip arming can support a higher boundary flow capability. In the current scheme, if an intertrip has existed for four years or more and where it is, in real time, operationally and commercially viable, then any resultant additional capability will now be applied to the 8 week ahead boundary limit. This removes from the constraint target any benefit produced by the arming of these intertrips. Intertrips that have existed for less than four years, however, are still not part of the baseline and could hence result in cost savings for National Grid
- We note that the inclusion of intertrips that are at least four years old as part of the baseline is the key reason why National Grid has proposed a significantly higher discount factor in this scheme (0.95) compared to the discount factor used in the previous scheme (0.62)
- For the purposes of this study, a detailed breakdown of the potential cost savings attributable to intertrips that have existed for four years or more compared to intertrips that are less than four years old was not made available to us. Any analytical evidence that can be provided to understand this breakdown would be particularly helpful with regards to justifying the proposed discount factor
- Moreover, it would also be important to understand if there is any potential for installing new intertrips during 2017/18 (which may result in additional cost savings), and if so to estimate what the resultant cost savings may be. From our discussions with National Grid, however, we understand that given the upfront costs and lead times to install new intertrips, it is unlikely that there will be significant opportunities for new intertrips during the 1-year scheme for 2017/18

Key findings and recommendations

Load participation factors

Load participation factors

- Load Participation Factors (LPFs) are used in the PLEXOS model to allocate the national demand in each period to individual network nodes. These LPFs are currently derived from data taken from a period when there was low PV and embedded wind output and are kept static throughout the year
- We would recommend carrying out additional analysis based on outturn data in order to understand how LPFs across different network locations change throughout the year and how those compare against the static LPF figures currently used in the model. Care should be taken to ensure that the contribution of PV and embedded generation is removed when considering LPFs.
- This could include for example the following comparison for all network nodes where LPFs are applied:
  - Ex-post hourly demand measured at GSP plus estimated PV and embedded generation; versus
  - National ex-post hourly demand (with appropriate adjustments for embedded generation) multiplied by existing LPF (which are static throughout the year)

Key findings and recommendations

Modelling of energy storage technologies

Modelling of pumped storage

- Pumped storage power stations in the PLEXOS model are dispatched based on price differentials only
- In reality, the operation of these power stations may be driven less by wholesale market revenue optimisation, and more by additional system requirements such as the provision of ancillary services
- We would therefore recommend additional analysis to be carried out to identify how accurately the half-hourly dispatch of pumped storage units in the PLEXOS model reflects outturn operation. If significant deviations are observed, the modelling approach may have to change in order to more closely account for their operation across the different markets they are participating in

Modelling of other energy storage technologies

- The role of storage in the GB electricity system is expected to increase with the move to a smart, low carbon system. Excluding pumped storage, there are a range of other energy storage technologies such as lithium ion batteries, flow batteries, super-capacitors, fly wheels, compressed air energy storage etc.
- Lithium ion batteries for example recently dominated the outcome of National Grid's 200MW Enhanced Frequency Response (EFR) tender, with the technology to be used for balancing services at grid scale for the first time in the UK
- The PLEXOS model does not currently include functionality for modelling non-Pumped Storage energy storage technologies. Due to the anticipated growth in such technologies over the coming years, we would recommend that this is a key item for further investigation in the future

Key findings and recommendations

Modelling of demand side flexibility

Dynamic thermal ratings

- The static rating of existing lines can be upgraded using more accurate assessment of the climatic conditions along the transmission network, or the lines can be rated in real time using a dynamic thermal rating system
- Dynamic thermal ratings are currently not included when setting PLEXOS transmission boundary limits. This is because limits are set 8 weeks ahead of real time and hence there is no certainty around whether dynamic ratings would be available to manage the system. Outages are planned and accepted on the system and flows need to be managed in the event of any number of situations arising in real time, including faults which happen between 8 week ahead and real time and will not be reflected in the limits
- With respect to access to these systems it is also important to note that dynamic thermal ratings are not the sole responsibility of the SO and rely on agreements between the SO and the Transmission Owners

Demand side flexibility

- Demand side flexibility (the ability of consumers to adapt their electricity consumption in response to an external signal) could represent a cost-efficient alternative to developing additional generation capacity
- Both large Industrial and Commercial (I&C) customers as well as customers from the residential and light commercial sector may provide demand side flexibility
- The 7 day ahead demand data that are used in the model do not account for any contribution from demand side flexibility. Moreover, the potential for demand side flexibility (reducing demand, increasing demand or shifting demand) is also not modelled in PLEXOS
- We would recommend demand side flexibility as an item for further investigation

Key findings and recommendations

Solar PV output in forward-looking models

Solar PV output in forward-looking models

- In the Year Ahead PLEXOS constraint models, the contribution of solar PV in the forward months is currently left blank. This is because historically there was no Year Ahead view of solar PV output available on a half hourly basis as it is so weather dependent, and because the PLEXOS model is designed as an outturn cost target model
- Even though this would have no impact on the scheme (as it is based on an outturn cost target model as explained above), we would recommend that for model testing purposes National Grid should instead consider using half hourly solar production data based on expected average conditions (e.g. by month or week) to allow the model to produce more meaningful forward-looking results
- Note that in the absence of any solar PV generation, the model would tend to overestimate the contribution of thermal power generation technology, typically gas-fired generation

Unconstrained analysis – Gas and coal

The 2016/17 unconstrained run overstates gas-fired generation at the expense of coal-fired generation

- Whilst plant availability and fuel/carbon prices in the PLEXOS model are ex-post, modelling of thermal power stations is based on a number of ex-ante data (such as plant efficiencies) together with any other commercial and technical considerations that may have an impact on the dispatch profile of these generators.
- We have compared the annual generation output from the unconstrained backcast 2016/17 PLEXOS run against the Final Physical Notifications (FPNs) submitted by generators over this period. The FPN for a BM Generator Unit is the level of export in a Settlement Period in the absence of any Balancing Mechanism Acceptances from the System Operator. Note that FPNs may be influenced by any actions National Grid has taken in the market pre-Gate Closure (which are not represented in the PLEXOS model). Whilst FPNs are not a perfect benchmark for the generation output from the unconstrained PLEXOS model, they can still be a useful proxy to understand how accurately the PLEXOS model dispatches generation units before network constraints are taken into account.
- It can be seen from the Table on the right that the unconstrained backcast 2016/17 PLEXOS run leads to a significant understatement of coal-fired generation relative to the FPNs submitted by these generators over this period. Conversely, gas-fired generation is higher in the PLEXOS model. In general, the affected coal generation is mainly located in Wales and Central/Northern England, whereas the affected gas generation is also located in Wales and Central/Northern England [✂].

Generation technology	Unconstrained PLEXOS run (TWh)	Sum of FPNs (TWh)	Difference (TWh)
Coal	11.6	23.9	+12.3
Gas	125.0	116.3	-8.7
COAL			
[✂]	2.6	7.1	+4.5
[✂]	5.2	7.8	+2.6
[✂]	0.5	2.6	+2.1
[✂]	0.3	1.6	+1.3
GAS			
[✂]	11.9	9.8	-2.0
[✂]	7.6	6.0	-1.7
[✂]	16.3	14.8	-1.5
[✂]	8.3	7.0	-1.3
[✂]	3.2	2.1	-1.1
[✂]	5.4	4.3	-1.1

Unconstrained analysis – Limitless run

The limitless run for the 2016/17 model produces identical results with the unconstrained run

- Constraint costs are estimated by running a PLEXOS simulation of the system unconstrained followed by a run with boundary limits included, using the result from the first run as the starting position of the generating units. The optimisation engine determines the generation output of the constrained system by identifying the minimum cost to move the system from the original position to a feasible position, given the transmission constraints.

- Prior to running a simulation of the constrained system, the model is also run with transmission boundary limits included but set to 99,999 MW for each boundary (i.e. such that boundary limits are never exceeded). This run is typically referred to as the "limitless" run and is carried out in order to test that the functionality of the model with respect to imposing transmission boundaries on the unconstrained run is as expected.

- We have reviewed the limitless run for the backcast 2016/17 PLEXOS model and we can confirm that, as expected, the limitless run produces identical results with the unconstrained run.

Backcast 2016/17 run			
Generation technology	Unconstrained run (TWh)	Limitless run (TWh)	Difference (TWh)
Coal	11.6	11.6	0.0
Gas	125.0	125.0	0.0
CHP	18.7	18.7	0.0
GT	0.0	0.0	0.0
Nuclear	67.1	67.1	0.0
PS	-0.9	-0.9	0.0
Hydro	3.0	3.0	0.0
Biomass	13.9	13.9	0.0
Wind	42.3	42.3	0.0
Solar	9.7	9.7	0.0

Constrained analysis – GB Boundaries in PLEXOS

Baringa

Constraints in the PLEXOS model typically arise due to constrained flows in [✂] boundaries

- The results presented here show the percentage of hours congested for the 10 most constrained transmission boundaries in the backcast 2016/17 PLEXOS model. Note that this is a relatively simplistic measure of transmission constraints as it does not show the flow volumes being constrained each hour, or the cost to the SO for resolving these constraints
- The [✂] boundary ([✂]) is the most heavily constrained transmission boundary in the 2016/17 PLEXOS model, and is constrained approximately 27% of the year
- Based on this metric, 6 out of the 10 most constrained boundaries in the model [✂]. Note that the [✂] generation mix contains significant volumes of relative inflexible renewable and nuclear generation
- The [✂] boundaries are also heavily constrained in the PLEXOS model. Note that flows across those boundaries will strongly depend on the operation of adjacent gas-fired power stations. As a result, given that the PLEXOS model tends to overstate gas-fired generation at the expense of coal-fired generation, it is also likely that it overestimates the extent to which these boundaries are constrained.
  - [✂] will have an influence on flows across the [✂] boundary;
  - [✂] will have an influence on flows across [✂];

Backcast 2016/17 run			
Boundary	Hours congested	% of hours congested	Location
[✂]	2,384	27%	[✂]
[✂]	1,992	23%	[✂]
[✂]	1,716	20%	[✂]
[✂]	1,603	18%	[✂]
[✂]	1,577	18%	[✂]
[✂]	1,469	17%	[✂]
[✂]	1,309	15%	[✂]
[✂]	1,032	12%	[✂]
[✂]	1,009	12%	[✂]
[✂]	696	8%	[✂]

Constrained analysis – Wind

Baringa

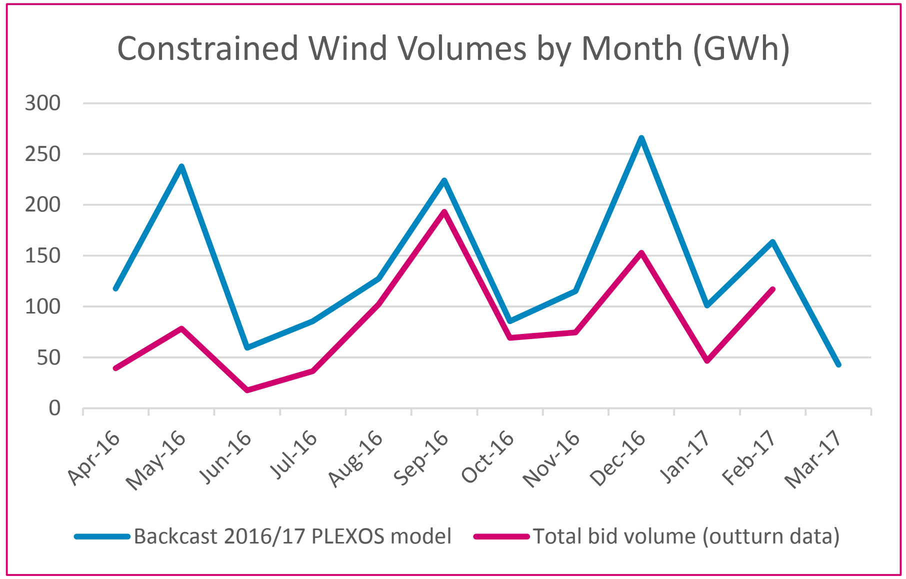
Constrained wind volumes in the backcast 2016/17 PLEXOS run are higher compared to historical data

- In the backcast 2016/17 PLEXOS run, the total volumes of wind generation that are being constrained in the PLEXOS model equal 1.63 TWh for the period 1st April 2016 to 31st March 2017. Monthly wind generation volumes increase throughout the year (as more wind capacity is added) however wind constrained volumes do not follow a specific pattern as can be seen in the Figure on the right

- We have looked at total bid volumes and total offer volumes for GB wind plant as reported by the NETA Reports web-service. These refer to bids and offers accepted by the SO for both System as well as Energy related purposes although for wind plant the former will dominate (for Q2-Q4 2016 for example 95% of all volumes on wind units were for System Balancing compared with 5% for Energy balancing)
  - Energy balancing actions: actions taken purely to balance the half hourly energy imbalance of the system
  - System balancing actions: actions taken for non-energy, system management reasons (e.g. to resolve transmission constraints)

- For the period 1st April 2016 to 28th February 2017, the total bid volume for GB wind equals 0.93 TWh of which we estimate that 0.89 TWh were due to System balancing actions. This compares against an equivalent volume of 1.58 TWh in the PLEXOS model. From our discussions with National Grid we understand that the backcast 2016/17 PLEXOS model uses Year Ahead boundary limits which may be significantly different compared to outturn boundary limits. Moreover, the PLEXOS model resolves all system congestion by simulated BM actions. In reality, however, a prudent SO may take additional measures to minimise constraint costs such as moving outages, trades with wind and intertrips

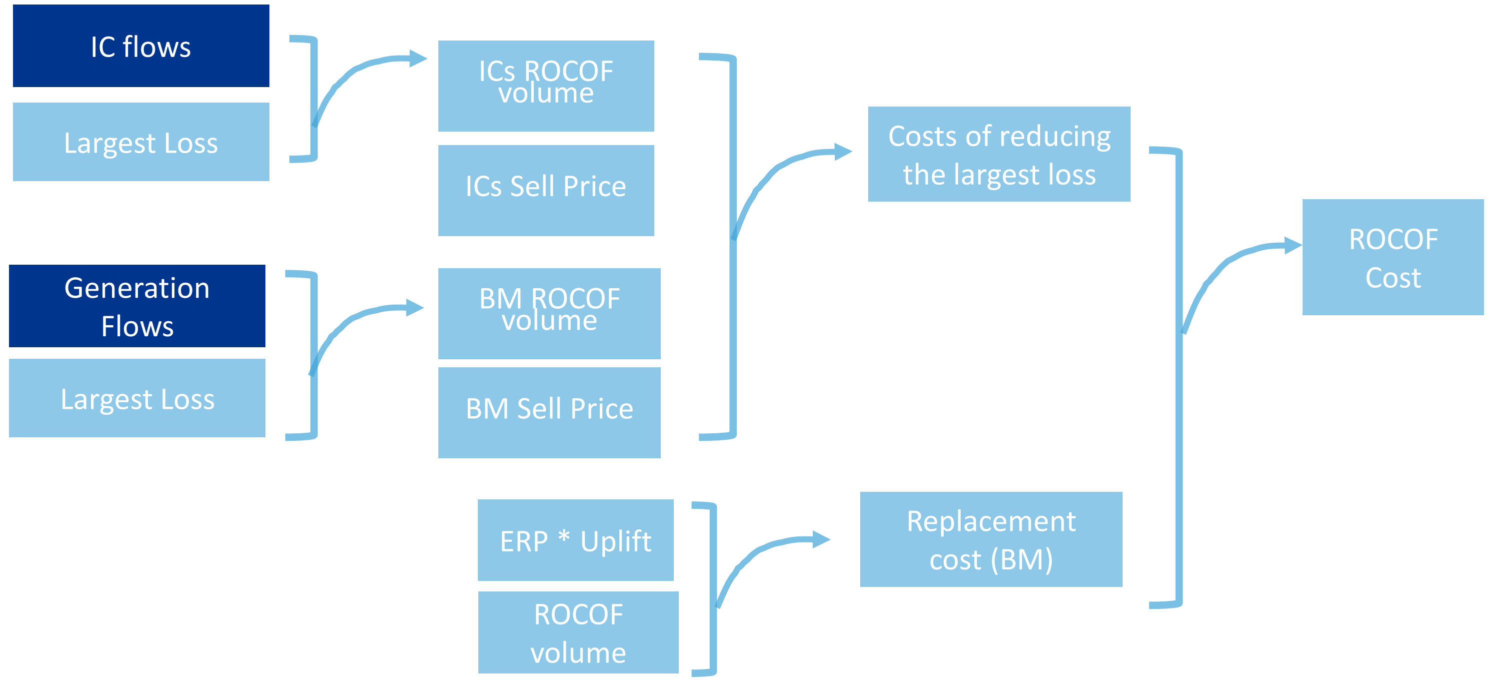
Backcast 2016/17 run	Volume (TWh)
Constrained Wind Volume	-1.63



Historical data (01/04/2016 to 28/02/2017)			
	Total Bid Volume (TWh)	Total Offer Volume (TWh)	Total Bid + Offer Volume (TWh)
Wind	-0.93	0.00	-0.93

Rate of Change of Frequency (ROCOF)

ROCOF_V_HH



Qualitative overview

- Rate of change of frequency (ROCOF) costs are incurred to ensure the system has sufficient inertia to respond to the largest credible loss. The SO will manage ROCOF by reducing the size of the largest instantaneous loss on the system, or by instructing generators which provide natural inertia onto the system. ROCOF costs are modelled using a deterministic model with outputs from PLEXOS.
- The HH ROCOF volume takes the constrained PLEXOS generation run and calculates the ‘largest loss’ for each half hour. This is then compared to flows on the interconnectors (ICs) and 5 key generator groups to calculate when these inputs are greater than the largest loss. Inertia provided is calculated as inertia provided by generation and demand.
- Prices used to calculate the costs of reducing the largest loss include a discount against the appropriate reference price, whereas replacement costs are calculated using an uplift factor.

17/18 changes

- The 17/18 model introduces more granular modelling of largest loss, and half-hourly modelling of demand inertia.

Key conclusions

Changes relative to previous scheme

- The key change relative to the previous scheme is the move to 8 week ahead transmission boundary limits (replacing year ahead limits) and 7 day ahead demand data (rather than year ahead). We expect this change to increase the accuracy of the model by using data closer to real time however, given that the related historical time series were not available to us, we were unable to quantify the expected reduction in forecast errors, and thus also the resultant improvement in model accuracy
- With respect to the Western HVDC Link, National Grid's proposed approach is that boundary flow limits assessed at 8 weeks ahead of scheduled commissioned date will have transfer capability assessed with both the Western HVDC Link available and unavailable, for the relevant boundaries affected. The ex post selection of the appropriate limit will then be built into the monthly process to best reflect system operation. We are satisfied that the proposed approach would not create an inherent bias when setting network constraint targets and we believe it is fit for purpose for future use

Recommendations for future years

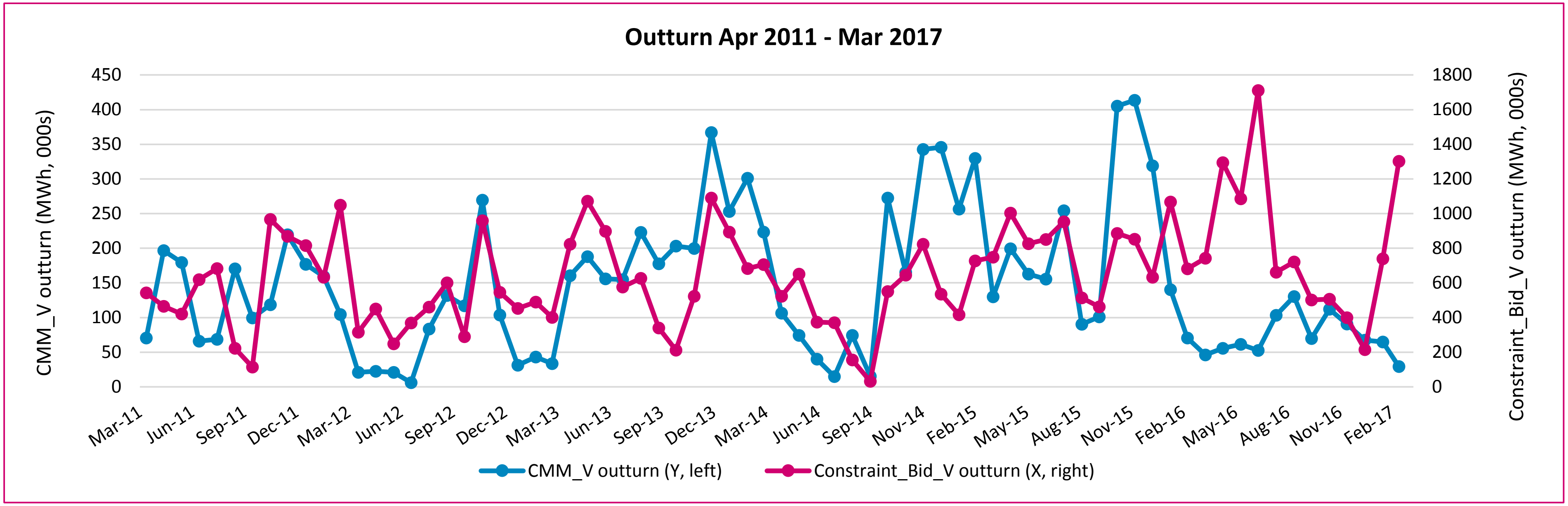
- The BSIS methodologies and models need to be capable of adapting to the evolving energy landscape. For the purposes of this study, we have made a number of recommendations such as the modelling of energy storage technologies (including battery storage) and demand side flexibility and the treatment of load participation factors as areas for further improvement

Appendix 1

Energy balancing models – further analysis

CMM Volume

CMM_V

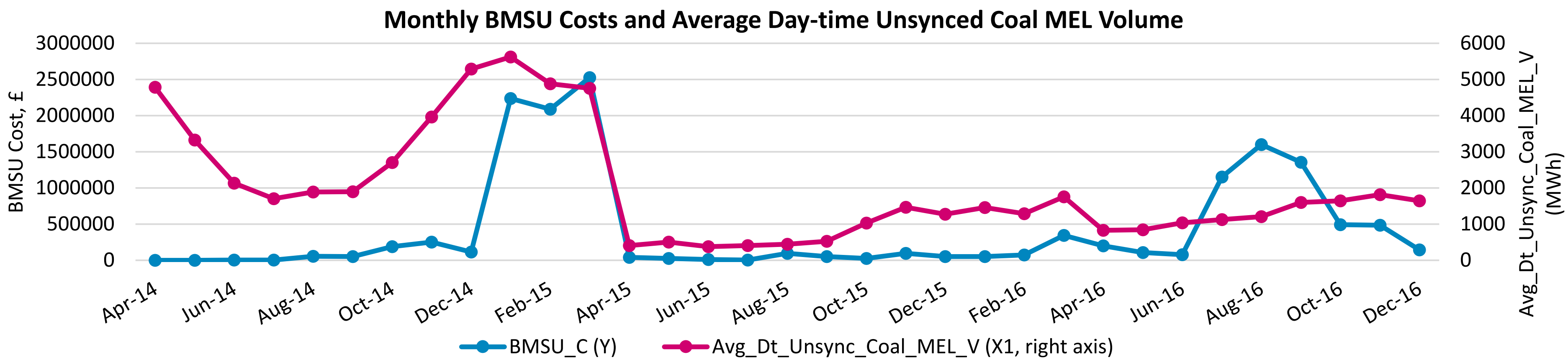


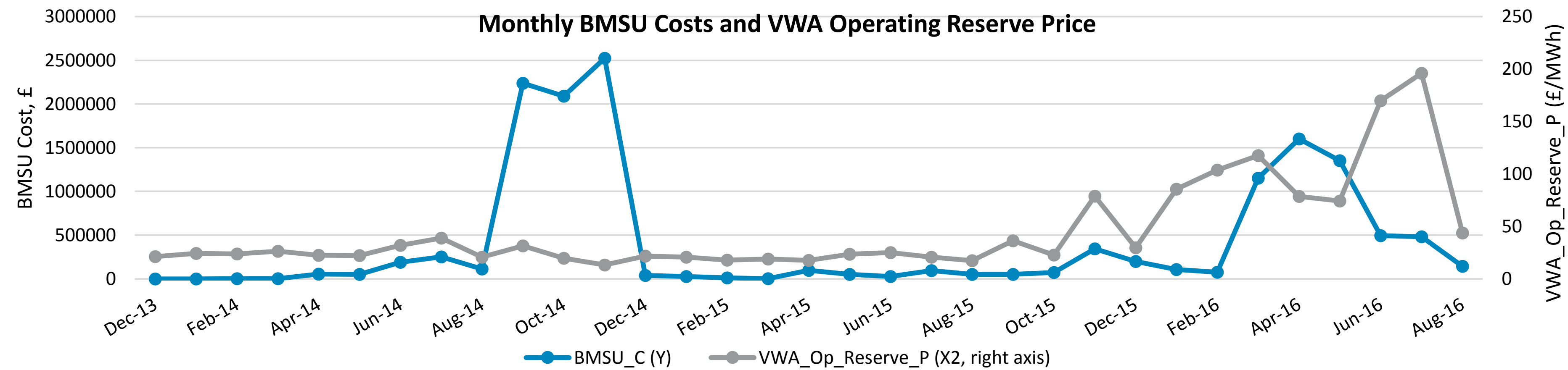
Overview

- This graph shows the relationship between CMM_V and Constraint_Bid_V on a monthly basis

BM Start-Up Cost

BMSU_C



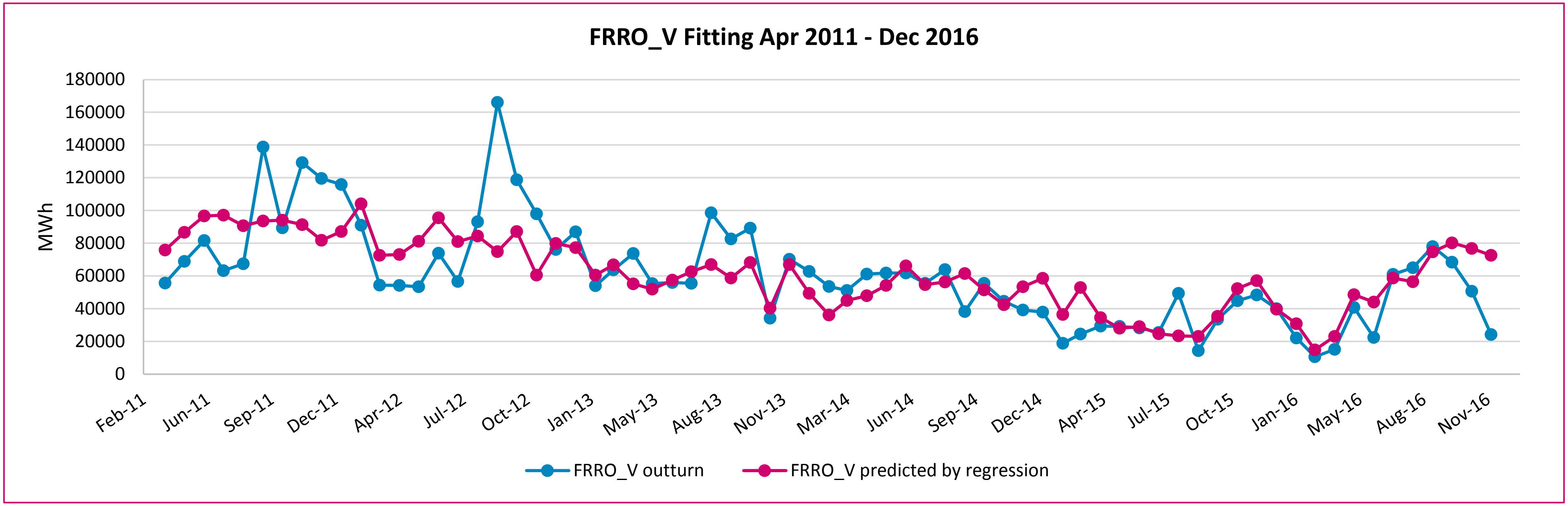


Overview

- These graphs show the relationship between average day-time unsycned coal MEL volumes and Balancing Mechanism Stat-Up (BMSU) costs by month, and Volume Weighted Average Operating Reserve Price and BMSU by month.

Frequency Response – Offer Volume

FRRO_V

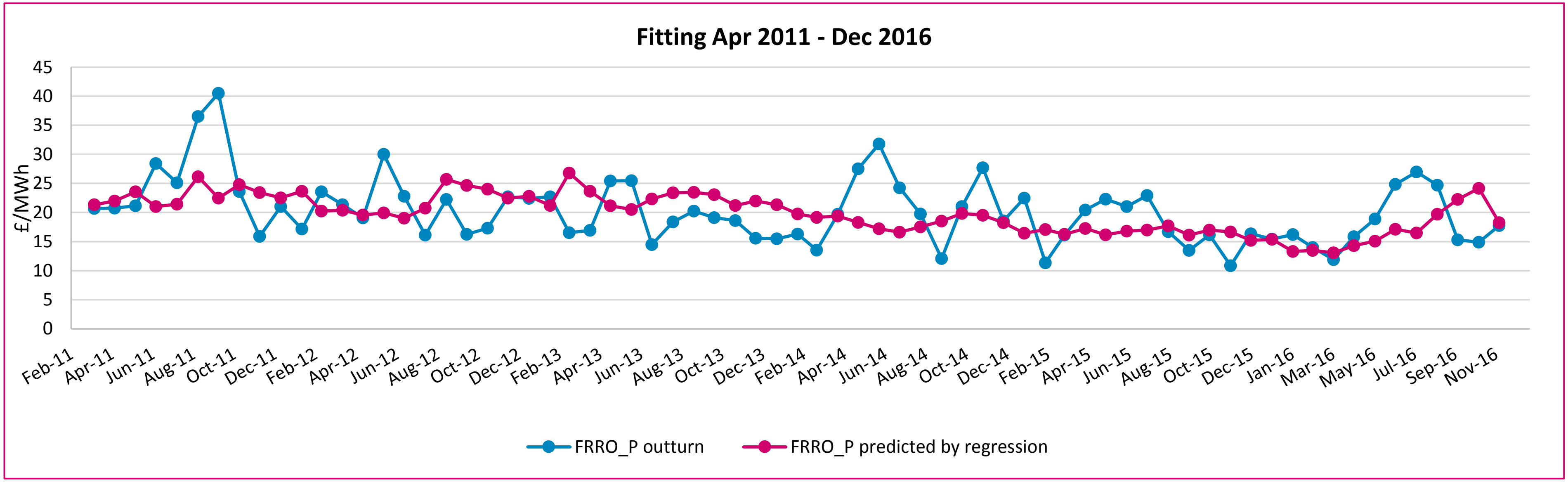


Overview

- This graph shows how volumes of Frequency Response Offer Volume (FRRO_V) predicted by the regression model fit to outturn FRRO_V by month.

Frequency Response – Offer Price

FRRO_P

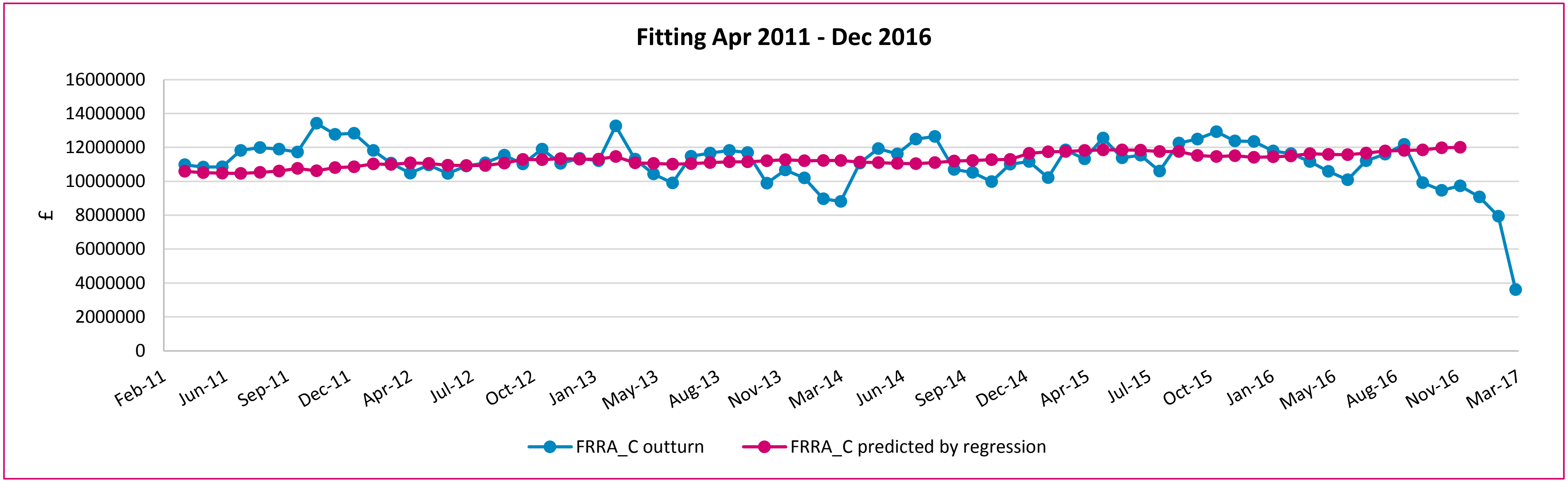


Overview

- This graph shows how Frequency Response Offer Prices (FRRO_P) predicted by the regression model fit to outturn FRRO_P.

Frequency Response – Ancillary Services Cost

FRRA_C

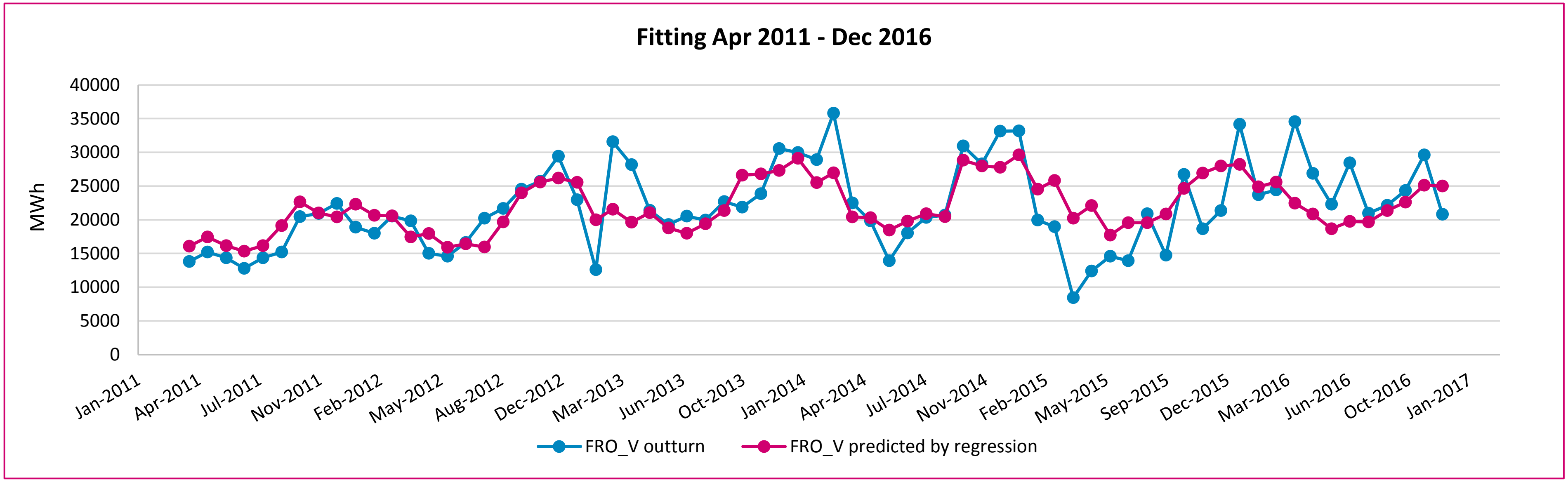


Overview

- This graph shows how Frequency Response Ancillary Services Costs (FRRA_C) predicted by the regression model fit to outturn FRRA_C costs.

Fast Reserve – Offer Volume

FRO_V

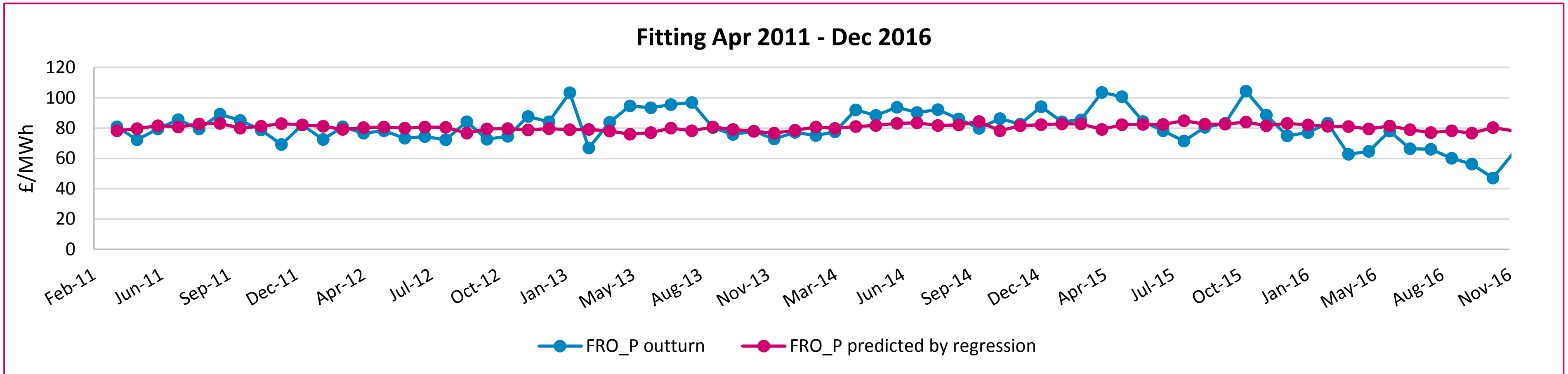


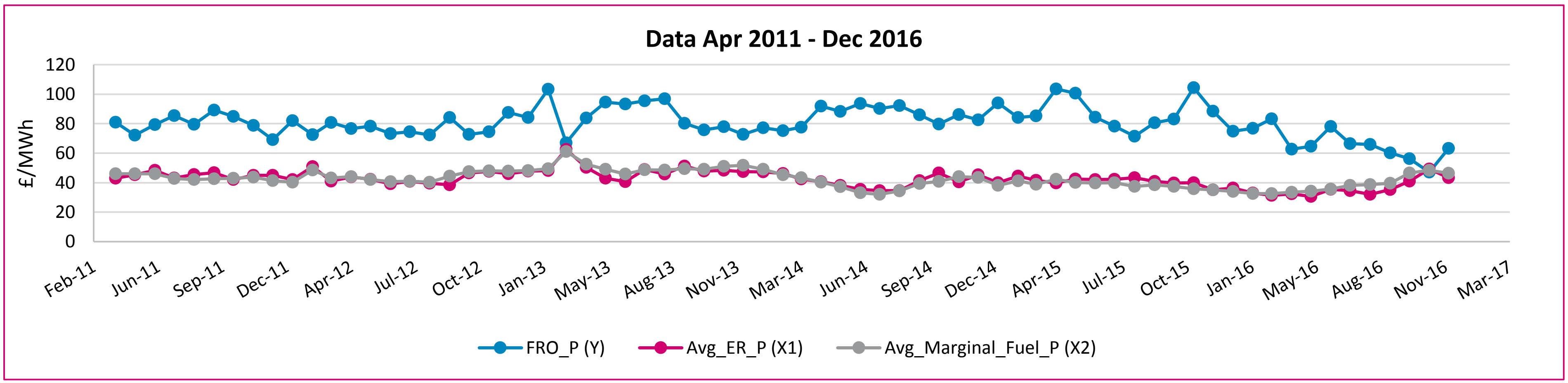
Overview

- This graph shows how Fast Reserve Offer Volumes (FRO_V) predicted by the regression model fit to outturn volumes by month.

Fast Reserve – Offer Price

FRO_P



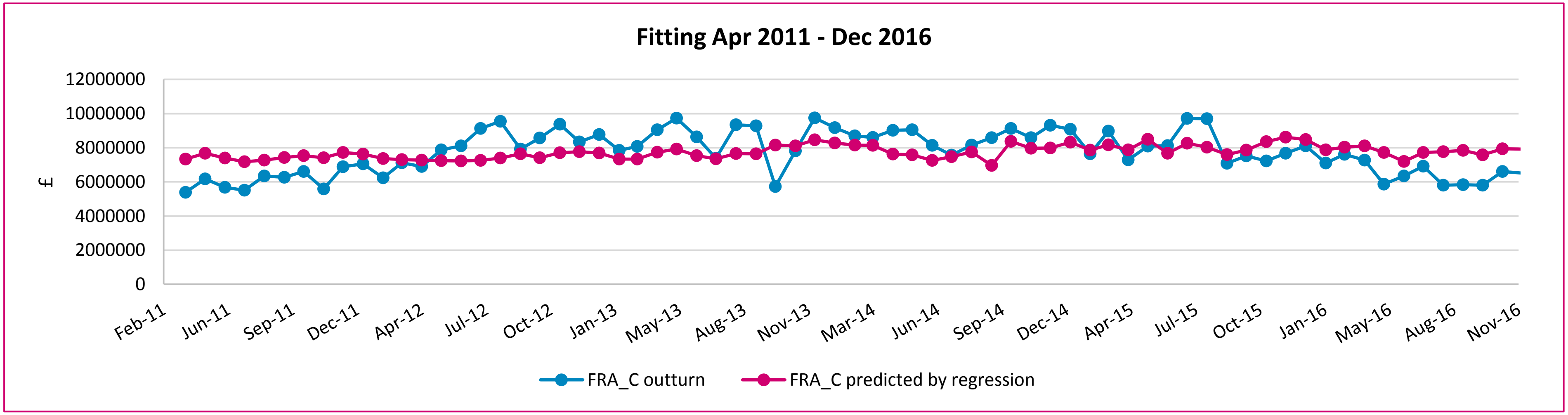


Overview

- These graphs show how Fast Reserve Offer Prices (FRO_P) predicted by the regression model match to outturn FRO_P values by month, and how FRO_Ps relate to the monthly average Energy Reference Price (ER_P) and the monthly Average Marginal Fuel Price (Avg_Marginal_Fuel).

Fast Reserve – Ancillary Services Cost

FRA_C

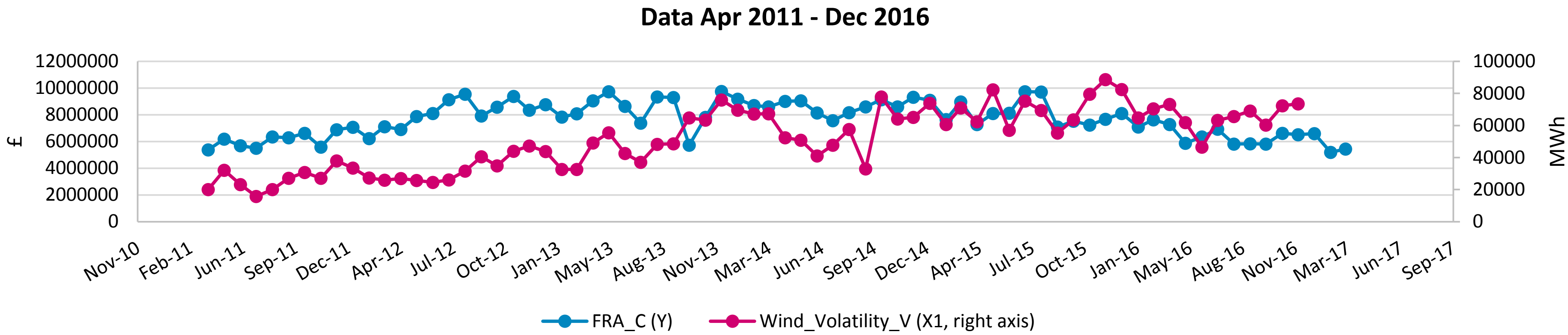


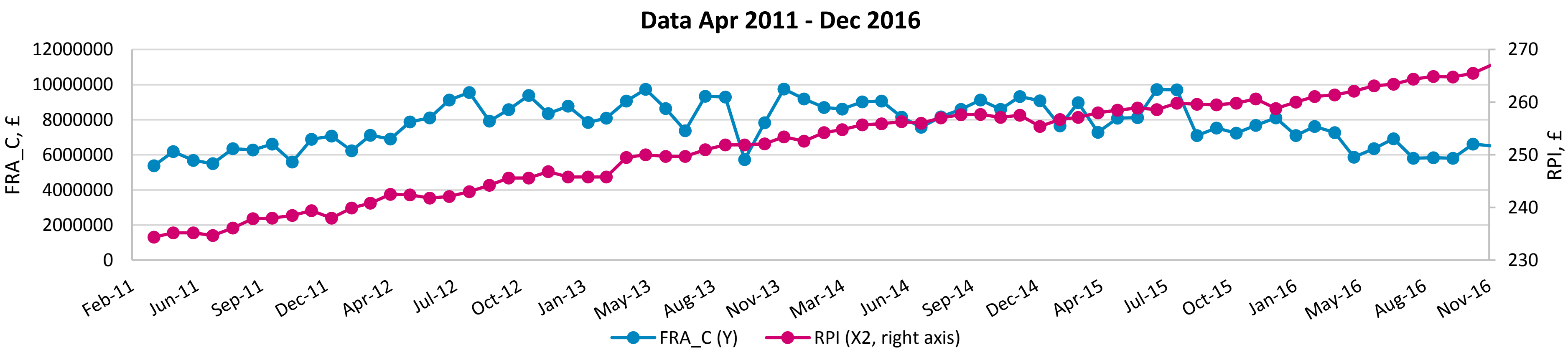
Assessment

- This graph shows how Fast Reserve Ancillary Costs (FRA_C) predicted by the regression fit to outturn costs by month.

Fast Reserve – Ancillary Services Cost

FRA_C



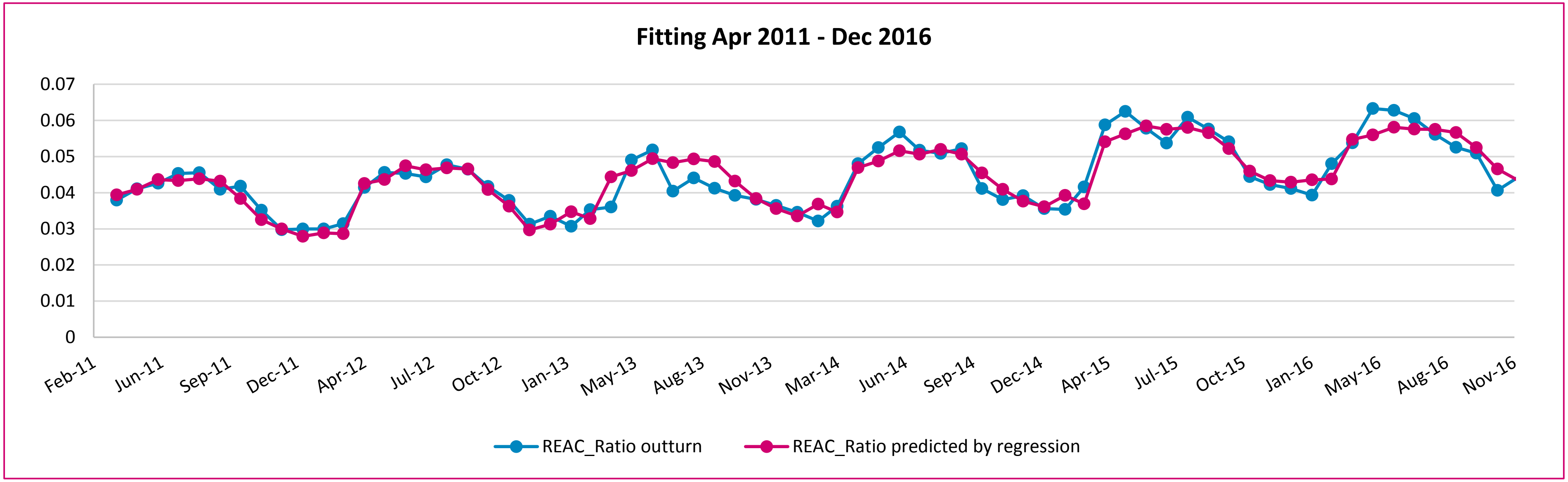


Assessment

- These graphs show the relationship between Fast Reserve Ancillary Costs (FRA_C) and wind volatility (wind_volatility_v), and FRA_C and the Retail Price Index (RPI).

Reactive Demand Ratio

REAC_Ratio

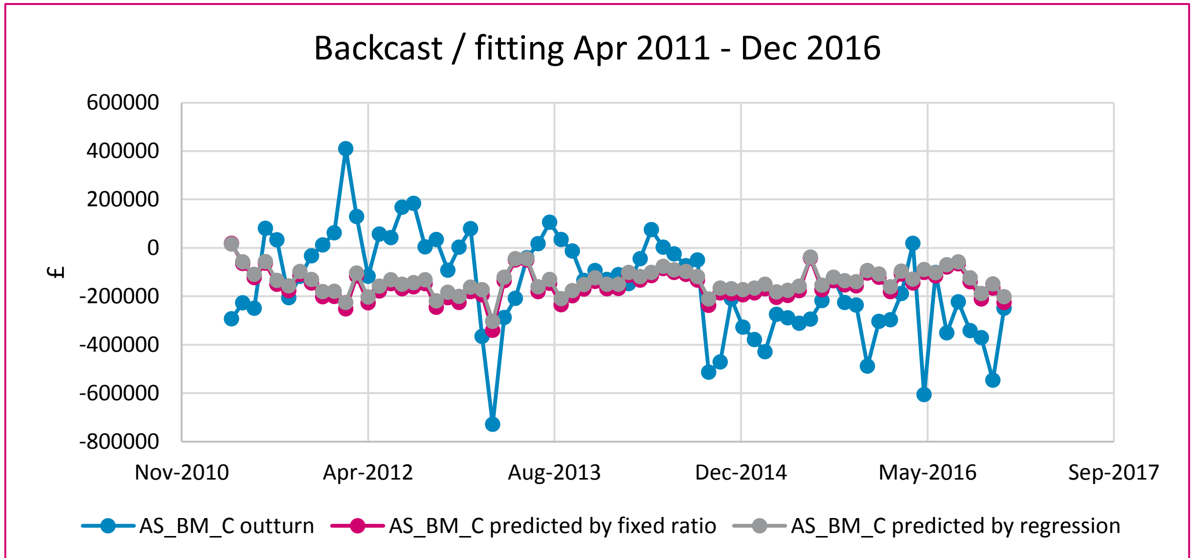


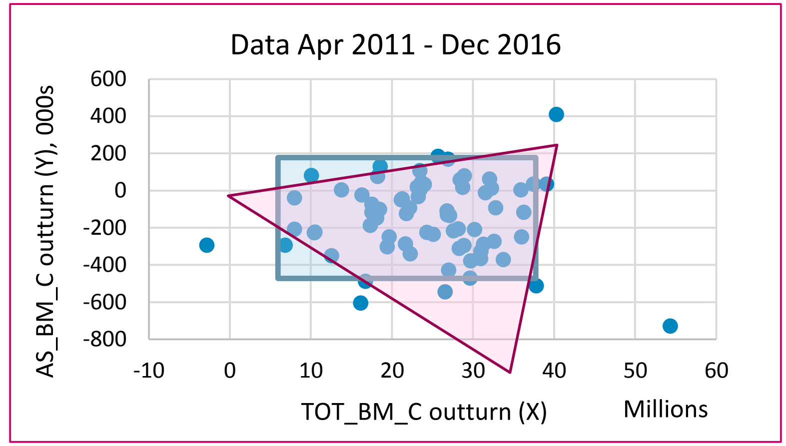
Assessment

- This graph shows the Reactive Demand Radio (REAC_Ratio) predicted by the regression compared to the outturn REAC_Ratio by month.

Ancillary Services & Balancing Mechanism General Cost

AS_BM_C





Overall performance	R^2
Overall fitting / prediction	0.33
Individual input performance	***p*-value**
C_0 Intercept (set to 0)	(N/A)
C_1 TOT_BM_C	~ 0

Assessment

- The first graph shows our regression analysis, and the SO's 'fixed ratio' approach. It shows that the trend of outturn AS_BM_C shifted from October 2014.
- The second graph shows the distribution of (TOT_BM_C, AS_BM_C). It shows that a linear model is unsuitable in this case.
- The results of our regression analysis are presented in the table

Balancing Mechanism Unclassified Cost

UN_BM_C

Overall performance		R^2
Overall fitting / prediction		0.83
Individual input performance		***p*-value**
C_0	Intercept (set to 0)	(N/A)
C_1	TOT_BM_C	~ 0

Assessment

- This table shows our regression analysis of UN_BM_C.

Brighter together