Dynamic Reserve Setting – Project Extension Evaluating the Effect of Additional Data Sets

Document SI23-P23-022
Version 1.0.1
19 April 2024

Contract NIA2\_NGESO003

|  |  |
| --- | --- |
| **Authors** | **Kieran Kalair** |
| **Internal reviewers** | **Alex Bowring** |
|  | **Jay Tarrant** |
|  | **Tom Wilson** |
|  | **Tim Boxer** |

Contents

[Context 9](#_Toc173248374)

[Value to ESO 9](#_Toc173248375)

[1 Introduction 10](#_Toc173248376)

[1.1 Model validation 10](#_Toc173248377)

[2 Key findings from the evaluation of new data sources 11](#_Toc173248378)

[3 Recommendations from experiments 13](#_Toc173248379)

[3.1 PV Live 16](#_Toc173248380)

[3.1.1 6hr ahead positive reserve model 16](#_Toc173248381)

[3.1.2 11am day-ahead positive reserve model 17](#_Toc173248382)

[3.1.3 8am day-ahead positive reserve model 17](#_Toc173248383)

[3.1.4 6hr ahead negative reserve model 17](#_Toc173248384)

[3.1.5 11am day-ahead negative reserve model 17](#_Toc173248385)

[3.1.6 8am day-ahead negative reserve model 18](#_Toc173248386)

[3.2 OCF Point forecasts 19](#_Toc173248387)

[3.2.1 6hr ahead positive reserve model 19](#_Toc173248388)

[3.2.2 11am day-ahead positive reserve model 19](#_Toc173248389)

[3.2.3 8am day-ahead positive reserve model 19](#_Toc173248390)

[3.2.4 6hr ahead negative reserve model 20](#_Toc173248391)

[3.2.5 11am day-ahead negative reserve model 20](#_Toc173248392)

[3.2.6 8am day-ahead negative reserve model 20](#_Toc173248393)

[3.3 Intensity of carbon on the system 22](#_Toc173248394)

[3.3.1 6hr ahead positive reserve model 22](#_Toc173248395)

[3.3.2 11am day-ahead positive reserve model 23](#_Toc173248396)

[3.3.3 8am day-ahead positive reserve model 23](#_Toc173248397)

[3.3.4 6hr ahead negative reserve model 23](#_Toc173248398)

[3.3.5 11am day-ahead negative reserve model 24](#_Toc173248399)

[3.3.6 8am day-ahead negative reserve model 24](#_Toc173248400)

[3.4 Difference between national demand forecasts 25](#_Toc173248401)

[3.4.1 6hr ahead positive reserve model 25](#_Toc173248402)

[3.4.2 11am day-ahead positive reserve model 25](#_Toc173248403)

[3.4.3 8am day-ahead positive reserve model 26](#_Toc173248404)

[3.4.4 6hr ahead negative reserve model 26](#_Toc173248405)

[3.4.5 11am day-ahead negative reserve model 26](#_Toc173248406)

[3.4.6 8am day-ahead negative reserve model 26](#_Toc173248407)

[3.5 Imbalance on the system 27](#_Toc173248408)

[3.5.1 6hr ahead positive reserve model 27](#_Toc173248409)

[3.5.2 11am day-ahead positive reserve model 28](#_Toc173248410)

[3.5.3 8am day-ahead positive reserve model 28](#_Toc173248411)

[3.5.4 6hr ahead negative reserve model 28](#_Toc173248412)

[3.5.5 11am day-ahead negative reserve model 29](#_Toc173248413)

[3.5.6 8am day-ahead negative reserve model 29](#_Toc173248414)

[3.6 Mix of generation on the system (DRS proxy) 30](#_Toc173248415)

[3.6.1 6hr ahead positive reserve model 30](#_Toc173248416)

[3.6.2 11am day-ahead positive reserve model 31](#_Toc173248417)

[3.6.3 8am day-ahead positive reserve model 31](#_Toc173248418)

[3.6.4 6hr ahead negative reserve model 31](#_Toc173248419)

[3.6.5 11am day-ahead negative reserve model 32](#_Toc173248420)

[3.6.6 8am day-ahead negative reserve model 32](#_Toc173248421)

[3.7 Mix of generation on the system (ESO API) 33](#_Toc173248422)

[3.7.1 6hr ahead positive reserve model 33](#_Toc173248423)

[3.7.2 11am day-ahead positive reserve model 34](#_Toc173248424)

[3.7.3 8am day-ahead positive reserve model 34](#_Toc173248425)

[3.7.4 6hr ahead negative reserve model 34](#_Toc173248426)

[3.7.5 11am day-ahead negative reserve model 35](#_Toc173248427)

[3.7.6 8am day-ahead negative reserve model 35](#_Toc173248428)

[3.8 European weather 36](#_Toc173248429)

[3.8.1 6hr ahead positive reserve model 36](#_Toc173248430)

[3.8.2 11am day-ahead positive reserve model 37](#_Toc173248431)

[3.8.3 8am day-ahead positive reserve model 37](#_Toc173248432)

[3.8.4 6hr ahead negative reserve model 37](#_Toc173248433)

[3.8.5 11am day-ahead negative reserve model 38](#_Toc173248434)

[3.8.6 8am day-ahead negative reserve model 38](#_Toc173248435)

[3.8.7 Manual hyperparameter selection 38](#_Toc173248436)

[3.9 OCF PVNet (without probabilistic features) 40](#_Toc173248437)

[3.9.1 6hr ahead positive reserve model 40](#_Toc173248438)

[3.9.2 11am day-ahead positive reserve model 41](#_Toc173248439)

[3.9.3 8am day-ahead positive reserve model 41](#_Toc173248440)

[3.9.4 6hr ahead negative reserve model 41](#_Toc173248441)

[3.9.5 11am day-ahead negative reserve model 41](#_Toc173248442)

[3.9.6 8am day-ahead negative reserve model 41](#_Toc173248443)

[3.10 OCF PVNet (with probabilistic features) 43](#_Toc173248444)

[3.10.1 6hr ahead positive reserve model 43](#_Toc173248445)

[3.10.2 11am day-ahead positive reserve model 44](#_Toc173248446)

[3.10.3 8am day-ahead positive reserve model 44](#_Toc173248447)

[3.10.4 6hr ahead negative reserve model 44](#_Toc173248448)

[3.10.5 11am day-ahead negative reserve model 44](#_Toc173248449)

[3.10.6 8am day-ahead negative reserve model 45](#_Toc173248450)

[4 Discussion of solar features in reserve setting 46](#_Toc173248451)

[4.1 Global feature importance for the reserve setting models 46](#_Toc173248452)

[4.2 6hr ahead positive reserve model 47](#_Toc173248453)

[4.3 11am day-ahead positive reserve model 48](#_Toc173248454)

[4.4 8am day-ahead positive reserve model 49](#_Toc173248455)

[4.5 6hr ahead negative reserve model 50](#_Toc173248456)

[4.6 11am day-ahead negative reserve model 51](#_Toc173248457)

[4.7 8am day-ahead negative reserve model 52](#_Toc173248458)

Document History

|  |  |  |
| --- | --- | --- |
| Version 1.0.1 | 19 April 2024: | Initial issue |
| Version 1.0.2 | 30 July 2024:  | Public report |

# Context

In the Spring of 2021, ESO contracted Smith Institute to prove the concept of using machine learning models to set reserve dynamically. These models used dynamic data such as forecasts of wind or other weather conditions at a day-ahead timescale to recommend reserve levels that would satisfy a given risk appetite and also provide the user of the model with an explanation for the recommendation made, highlighting which dynamic factors were the key drivers of the recommendation made. This proof-of-concept phase of the Dynamic Reserve Setting (DRS) project showed that dynamic reserve modelling could save ESO around 300MWs per settlement period when compared to ESO’s current static model.

Given the substantial saving this modelling approach could make, it was decided that it would be worthwhile to investigate what further gains in MW savings could be made by considering different forecasts and features in the model with negligible degradation of the risk performance. In investigating this, a process could be developed that, given a new forecast, quantified the impact this forecast had on reserve setting, specifically if this forecast led to an increase in MW savings or risk performance. Solar forecasting was considered to be an area of particular interest by ESO. As a result, a change request for the DRS project was processed and ESO contracted with Open Climate Fix (OCF) to provide an additional PV forecast dataset. Smith Institute constructed a method for evaluating a candidate data set, re-training the models after the data had been included and evaluating the impact of the new data on the models for DRS. This new phase of work concluded by carrying out the designed process and quantifying the value of different data sources in reserve setting and made recommendations about possible fruitful investigation pathways for future improvements in the reserve setting methodology.

## Value to ESO

The PoC DRS developed in the main phase of the project was shown to deliver significant MW savings compared to the historic reserve setting approach whilst adhering to specified risk appetites, modelling reserve both day ahead and within day. . This means the developed dynamic method of reserve setting could lower the operational costs for ESO whilst not impacting security of the grid, showing that they are active in their mandate to operate more efficiently in the future.

Value has also been delivered in the extension of this project. The process of evaluating the impact of a particular dataset in the context of reserve setting is now replicable and has been showcased on a variety of candidate datasets, identifying key areas to explore to improve reserve setting in the future. As improved or entirely new forecasts and datasets become available in the future, ESO are now in a position to quantify the value of these in the context of reserve setting. This will also help ESO to act in an efficient manner, as there is now an objective way of concluding which candidate datasets are of particular interest to integrate into their systems.

1. Introduction

In this phase, we explore the extent to which additional and improved forecast data sources may be able to provide further MW savings while still maintaining the same level of risk performance in securing the grid. Specifically, the current phase of work for the DRS project focuses on answering the question: ***what value can be quantified when considering procuring additional data sources and improved forecasts?*** Since November 2023, a process to answer such a question has been designed and implemented on several candidate datasets.

This report provides a high-level summary of the analyses from this phase of the project, demonstrating the process in action and quantifying the improvement to the DRS models that was obtained when different data sources were made available as features to the model.

* 1. Model validation

Throughout this phase of the project, we use the term ‘experiment’ to refer to investigations of the impact that new or improved data sources and forecasts have on the dynamic reserve setting models. For example, one experiment is to include in the candidate feature set information about the mix of generation on the system, and then tune, fit and evaluate the reserve setting models with this new information. The models considered include the 6hr ahead, 11am day-ahead and 8am day-ahead models, for both positive and negative reserve. Each time an experiment has been completed; we validate the resulting models to assess the impact of the new data. We consider the following during validation, for each model:

* How does empirical model risk appetite match the target risk appetite?
* How does the amount of excess MWs recommended compare between the DRS approach and the historic approach (denoted model sharpness)?
* On average, how many MWs per settlement period are saved, compared to the equivalent static model by using the dynamic model?
* How does risk performance vary through time?
* How do MW savings vary through time?
* How does performance vary by time of day and season?

All results discussed are for models targeting the 0.997 quantile when considering positive reserve (URE) and the 0.003 quantile when considering negative reserve (DRE). The results have been generated by using the experiment pipeline in the DRS codebase, and performing expanding window cross validation, to ensure no future data is used to predict the past. Whenever changes in dynamic model quality are discussed and shown, these are changes compared to the DRS models from previous phases of work that were trained using features already collected by ESO. We have fixed random seeds in the experiment pipeline to ensure repeatability where possible. However, the non-linearity of the models, fitting procedure and hyper-parameter tuning process may mean slightly different results are observed if the tests are re-run on different computational architectures.

1. Key findings from the evaluation of new data sources

Here we summarise the key findings from our evaluation of using different data sources in the context of reserve setting.

1. We identified several completely new data sources (not just improvements on current forecasts used for reserve setting) that show promising signs in terms of model improvement:
	1. Perfect knowledge of system imbalance shows significant MW savings without significant decreases in risk performance. If it is possible to accurately forecast this variable, then it may be of significant use for reserve setting.
	2. Perfect knowledge of generation mix, particularly the amount of wind and interconnector output on the system show improvements to numerous reserve setting models. From our analysis, knowing the percentage of each type of generation on the system is not as important to reserve setting as simply knowing the amount of wind and interconnector generation.
2. Wind is a significant driver in the models for reserve setting, with several wind features appearing among the most important features in multiple models. If ESO can improve their existing wind forecasts across the country, this could lead to a significant improvement in reserve setting performance.
3. The exact influence of a given feature cannot be isolated. Many features are correlated (or non-linearly related) with other features to some small degree, even though highly correlated inputs are filtered during model feature selection. Information about the current solar state is implied by numerous features in the model, for example: time of day, season, air temperature and wind. Therefore, one cannot answer questions of the form ‘what is the influence of a single solar feature on reserve settings’. Instead, what can be done with the pipeline and tools developed is to answer, ‘If we use solar forecast X instead of solar forecast Y, how does the risk performance and MW savings of the reserve setting model change?’.
4. Adding or removing features from the candidate feature set can lead to a significant change in the final model one arrives at. This is due to the non-linearity and complexity in the feature selection, hyper-parameter tuning and final model fitting process. When fitting a new model, a feature set is selected based on importance values for features, judged by the frequency with which a feature is used in the gradient boosted tree model. Features that are sufficiently important are retained, and hyper-parameters for a final model are tuned to optimise quantile loss. Automated tuning for all model hyper-parameters in the implementation of gradient boosted trees is not available, and one must pre-specify a small number of hyper-parameters, whilst tuning the remaining ones. When altering the feature set the model can use, these manually specified hyper-parameters can have a significant influence of the quality of the final model. In particular, some choices can lead to poor risk performance. When experimenting with new data, we suggest trying multiple sets of these manually specified parameters, particularly if a large number of candidate features are being added to the feature set.
5. It may be useful to explore alternative measures of feature importance when refining the set of candidate features the model must use in the future. Feature importance during model tuning is currently computed based on the number of trees that a feature appears in within the ensemble of trees that constitute the model. Model selection is a fundamental problem in all machine learning tasks, and it may be that exploring alternative measures of feature importance can result in an improved model.
6. Recommendations from experiments

A summary of recommendations for each experiment run can be found in the table below, with further details given in the subsequent subsections of this section. All recommendations are based on the joint impact of risk performance & MW savings of the model arrived at after running the experiment pipeline.

|  |  |
| --- | --- |
| Data source / candidate feature(s) | **Impact on reserve setting models** |
| PV Live | Perfect knowledge of solar outturns (as defined by PV live, which may still be subject to some level of error) improve the 6hr ahead positive reserve and 11am day ahead negative reserve models. However, embedded solar output does not appear to be a major driver in the reserve setting models. |
| OCF point forecasts | Replacing existing ESO national level solar forecasts from PEF with OCF point forecasts does not appear to improve performance of any the positive reserve setting models. There are very minor changes for the 6hr ahead and 11am day-ahead negative reserve models, but the largest improvement is seen with the 8am day-ahead negative reserve setting model. |
| Intensity of carbon on the system | Knowledge of carbon intensity improves the risk performance of the 8am day-ahead positive reserve model and the MW savings of the 11am day-ahead negative reserve model. In the latter case, it does so without impacting risk performance at all. However, knowledge of carbon intensity does not appear to provide substantial MW savings from the other models without degrading the risk performance. Rather than invest resources in forecasting carbon intensity, ESO may be better placed investing in forecasts of generation mix (see later experiments) which capture a more fine-grained understanding of carbon on the system. |
| Difference between national demand forecasts | There is no benefit from including this in the reserve setting models.  |
| Imbalance on the system | Knowledge of system imbalance is a significantly impactful feature for reserve modelling, and perfect knowledge of this improved the performance (increased MW savings with little to no impact on risk performance) of several models. ESO may wish to explore if accurate models of system imbalance can be built, as our results suggest this could result in significant savings for reserve modelling. |
| Mix of generation on the system (DRS proxy) | Knowledge of generation mix (derived using actuals already in the DRS database) improves the risk performance of the 11am day-ahead positive reserve model and leads to modest MW savings for several other models without impacting risk significantly. Importantly, the amount of wind and interconnector flow on the system appear to be particularly useful to know. |
| Mix of generation on the system (ESO API) | Knowledge of generation mix (taken using the definition from the ESO API) improves risk performance on all positive reserve setting models, but as a result leads to less MW savings. The 11am day-ahead positive reserve setting model in-particular shows a much closer (to the target risk) empirical risk appetite when given knowledge of the generation mix. This data has little impact on the negative reserve models. Importantly, the amount of wind and imports on the system appear to be particularly useful. |
| European weather | The approaches considered to incorporate European weather data into reserve modelling do not improve the reserve setting models without compromising their risk performance. Incorporating European weather data presents multiple challenges, namely, how to best aggregate the weather information across the continent, and how to ensure the size of the feature set remains reasonable when incorporating this information. Providing the reserve setting models with a huge candidate feature set can lead to overfitting and issues with feature selection. If ESO wish to improve reserve setting through incorporation of EU weather data, these challenges must be further investigated. |
| OCF PVNet (without probabilistic features) | Using the point forecasts provided by OCF, which we understand to be a blend of the PVNet model and a gradient boosted tree model (depending on lead time), achieves better risk performance for the 11am day-ahead positive reserve model, however this comes at the cost of fewer MW savings. For all other reserve setting models, there is no significant benefit in including the OCF forecasts in-place of ESO’s existing solar forecasts, without a significant degradation in risk performance. Comparing this to the probabilistic results (see entry below), there is clearly benefit in quantifying uncertainty in solar forecasts, rather than improving point-wise estimates with regards to reserve setting. |
| OCF PVNet (with probabilistic features) | Here we consider using the point forecasts provided by OCF in conjunction with probabilistic forecasts they provide, which we understand to be a blend of the PVNet model and a gradient boosted tree model (depending on lead time). When using these, we see an improvement in the MW savings for the 6hr ahead and 11am day-ahead positive reserve models, with only a small corresponding drop in risk performance. For all other reserve setting models, the provided solar forecasts with the probabilistic information do not appear to improve the reserve setting models performance when compared to simply using existing ESO forecasts. If ESO wish to improve their solar forecasts in the future, it appears capturing a measure of uncertainty in predictions at each time is useful for reserve setting purposes. |

Table : Summary of experiment results.

* 1. PV Live

Full details found in November 2023 progress report.

|  |  |  |  |
| --- | --- | --- | --- |
| Model | **Target** | **Impact on Risk (compared to baseline model)** | **Impact on MW saving per settlement period (compared to baseline model)** |
| 6hr ahead | Positive reserve | Negligible degradation | 64MW saving  |
| 11am day-ahead | Positive reserve | Degradation  | 24MW saving |
| 8am day-ahead | Positive reserve | No PV Live features selected during fitting | No PV Live features selected during fitting |
| 6hr ahead | Negative reserve | Negligible degradation | 10MW decrease |
| 11am day-ahead | Negative reserve | Negligible degradation | 56MW saving |
| 8am day-ahead | Negative reserve | No PV Live features selected during fitting | No PV Live features selected during fitting |

Table : Analysis of the impact of PV live data on reserve setting models.

* + 1. 6hr ahead positive reserve model
* Including PV Live solar outturns for the 6hr ahead, positive reserve model shows a slight degradation in risk performance, but saves more MWs compared to the model without PV Live solar outturns
* With perfect knowledge of PV Live solar outturns, the 6hr ahead, positive reserve setting model would perform very slightly worse in terms of risk appetite, but would show a higher MW saving as a result of this compared to the alternative model
* Empirical risk (without PV Live solar outturns): 0.006
* Empirical risk (with PV Live solar outturns): 0.007
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without PV Live solar outturns): 266MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with PV Live solar outturns): 330MW
	+ 1. 11am day-ahead positive reserve model
* Including PV Live solar outturns for the 11am day-ahead, positive reserve model shows a degradation in risk performance, and as a result of this increases the number of MWs saved compared to the model without PV Live solar outturns
* With perfect knowledge of PV Live solar outturns, the 11am day-ahead, positive reserve setting model would stray further from the desired risk appetite, but would show a higher MW saving as a result of this compared to the alternative model
* Empirical risk (without PV Live solar outturns): 0.011
* Empirical risk (with PV Live solar outturns): 0.014
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without PV Live solar outturns): 541MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with PV Live solar outturns): 565MW
	+ 1. 8am day-ahead positive reserve model
* No PV Live features were selected by the feature selection procedure for this experiment, so no results are reported
	+ 1. 6hr ahead negative reserve model
* Including PV Live solar outturns for the 6hr ahead, negative reserve model shows no change in risk performance, but a slight decrease in the number of MWs saved compared to the model without PV Live solar outturns
* With perfect knowledge of PV Live solar outturns, the 6hr ahead, negative reserve setting model would operate at the same risk level, but save slightly fewer MWs compared to the alternative model
* Empirical risk (without PV Live solar outturns): 0.995
* Empirical risk (with PV Live solar outturns): 0.995
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without PV Live solar outturns): 196MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with PV Live solar outturns): 186MW
	+ 1. 11am day-ahead negative reserve model
* Including PV Live solar outturns for the 11am day-ahead, negative reserve model shows no change in risk performance, but an increase in the number of MWs saved compared to the model without PV Live solar outturns
* With perfect knowledge of PV Live solar outturns, the 11am day-ahead, negative reserve setting model would operate at the same risk appetite, but save more MWs compared to the alternative model
* Empirical risk (without PV Live solar outturns): 0.994
* Empirical risk (with PV Live solar outturns): 0.994
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without PV Live solar outturns, lead time <= 10 hours): 150MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with PV Live solar outturns, lead time <= 10 hours): 206MW
	+ 1. 8am day-ahead negative reserve model
* No PV Live features were selected by the feature selection procedure for this experiment, so no results are reported
	1. OCF Point forecasts

Full details found in December 2023 progress report.

|  |  |  |  |
| --- | --- | --- | --- |
| Model | **Target** | **Impact on Risk (compared to baseline model)** | **Impact on MW saving per settlement period (compared to baseline model)** |
| 6hr ahead | Positive reserve | No OCF point forecast features selected during fitting | No OCF point forecast features selected during fitting |
| 11am day-ahead | Positive reserve | No OCF point forecast features selected during fitting | No OCF point forecast features selected during fitting |
| 8am day-ahead | Positive reserve | Degradation | 133MW saving (due to degradation in risk) |
| 6hr ahead | Negative reserve | No change | 12MW saving |
| 11am day-ahead | Negative reserve | No change | 2MW saving |
| 8am day-ahead | Negative reserve | No change | 54MW decrease |

Table : Analysis of the impact of OCF point forecast data on reserve setting models. For a full list of features selected, see associated progress report.

* + 1. 6hr ahead positive reserve model
* No PV Live features were selected by the feature selection procedure for this experiment, so no results are reported
	+ 1. 11am day-ahead positive reserve model
* No PV Live features were selected by the feature selection procedure for this experiment, so no results are reported
	+ 1. 8am day-ahead positive reserve model
* Including OCF point forecasts for the 8am day-ahead, positive reserve model shows an improvement in risk performance, and as a result of this decreases the number of MWs saved compared to the model without OCF point forecasts
* With OCF point forecasts instead of ESO’s PEF solar forecasts, the 8am day-ahead, positive reserve setting model would stray further from the desired risk appetite, but would show a greater MW saving as a result of this compared to the alternative model
* Empirical risk (without carbon intensity): 0.008
* Empirical risk (with carbon intensity): 0.011
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without carbon intensity): 355MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with carbon intensity): 488MW
	+ 1. 6hr ahead negative reserve model
* Including OCF point forecasts for the 6hr ahead, negative reserve model shows no change in risk performance, but a slight increase in the number of MWs saved compared to the model without OCF point forecasts
* With OCF point forecasts instead of ESO’s PEF solar forecasts, the 6hr ahead, negative reserve setting model would operate at the same risk level, but save slightly more MWs compared to the alternative model
* Empirical risk (without OCF point forecasts): 0.995
* Empirical risk (with OCF point forecasts): 0.995
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without OCF point forecasts): 196MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with OCF point forecasts): 208MW
	+ 1. 11am day-ahead negative reserve model
* Including OCF point forecasts for the 11am day-ahead, negative reserve model shows no change in risk performance, but a slight increase in the number of MWs saved compared to the model without OCF point forecasts
* With OCF point forecasts instead of ESO’s PEF solar forecasts, the 11am day-ahead, negative reserve setting model would operate at the same risk appetite, but save very slightly more MWs compared to the alternative model
* Empirical risk (without OCF point forecasts): 0.994
* Empirical risk (with OCF point forecasts): 0.994
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without OCF point forecasts, lead time <= 10 hours): 150MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with OCF point forecasts, lead time <= 10 hours): 152MW
	+ 1. 8am day-ahead negative reserve model
* Including OCF point forecasts for the 8am day-ahead, negative reserve model shows no change in risk performance, but a decrease in the number of MWs saved compared to the model without OCF point forecasts information
* With OCF point forecasts instead of ESO’s PEF solar forecasts, the 8am day-ahead, negative reserve setting model would operate at the same risk appetite, but save fewer MWs compared to the alternative model
* Empirical risk (without OCF point forecasts): 0.994
* Empirical risk (with OCF point forecasts): 0.994
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without OCF point forecasts, lead time <= 10 hours): 209MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with OCF point forecasts, lead time <= 10 hours): 155MW
	1. Intensity of carbon on the system

Full details found in January 2024 progress report.

|  |  |  |  |
| --- | --- | --- | --- |
| Model | **Target** | **Impact on Risk (compared to baseline model)** | **Impact on MW saving per settlement period (compared to baseline model)** |
| 6hr ahead | Positive reserve | Degradation  | 230MW saving (due to degradation in risk) |
| 11am day-ahead | Positive reserve | Significant degradation | 341MW saving (due to degradation in risk) |
| 8am day-ahead | Positive reserve | Improvement | 91MW degradation (due to improvement in risk) |
| 6hr ahead | Negative reserve | No change | 10MW degradation  |
| 11am day-ahead | Negative reserve | No change | 32MW saving |
| 8am day-ahead | Negative reserve | No change | 90MW degradation  |

Table : Analysis of the impact of intensity of carbon data on reserve setting models. For a full list of features selected, see associated progress report.

* + 1. 6hr ahead positive reserve model
* Including carbon intensity for the 6hr ahead, positive reserve model shows a degradation in risk performance, and as a result of this saves more MWs compared to the model without carbon intensity information
* With perfect knowledge of carbon intensity, the 6hr ahead, positive reserve setting model would not meet the desired risk appetite, but would show a higher MW saving as a result of this compared to the alternative model
* Empirical risk (without carbon intensity): 0.006
* Empirical risk (with carbon intensity): 0.01
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without carbon intensity): 266MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with carbon intensity): 469MW
	+ 1. 11am day-ahead positive reserve model
* Including carbon intensity for the 11am day-ahead, positive reserve model shows a degradation in risk performance, and as a result of this increases the number of MWs saved compared to the model without carbon intensity information
* With perfect knowledge of carbon intensity, the 11am day-ahead, positive reserve setting model would not meet the desired risk appetite, but would show a higher MW saving as a result of this compared to the alternative model
* Empirical risk (without carbon intensity): 0.011
* Empirical risk (with carbon intensity): 0.021
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without carbon intensity): 541MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with carbon intensity): 882MW
	+ 1. 8am day-ahead positive reserve model
* Including carbon intensity for the 8am day-ahead, positive reserve model shows an improvement in risk performance, and as a result of this decreases the number of MWs saved compared to the model without carbon intensity information
* With perfect knowledge of carbon intensity, the 8am day-ahead, positive reserve setting model would better meet the desired risk appetite, but would show a lower MW saving as a result of this compared to the alternative model
* Empirical risk (without carbon intensity): 0.008
* Empirical risk (with carbon intensity): 0.006
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without carbon intensity): 355MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with carbon intensity): 264MW
	+ 1. 6hr ahead negative reserve model
* Including carbon intensity for the 6hr ahead, negative reserve model shows no change in risk performance, but a slight decrease in the number of MWs saved compared to the model without carbon intensity information
* With perfect knowledge of carbon intensity, the 6hr ahead, negative reserve setting model would operate at the same risk level, but save slightly fewer MWs compared to the alternative model
* Empirical risk (without carbon intensity): 0.995
* Empirical risk (with carbon intensity): 0.995
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without carbon intensity): 196MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with carbon intensity): 186MW
	+ 1. 11am day-ahead negative reserve model
* Including carbon intensity for the 11am day-ahead, negative reserve model shows no change in risk performance, but an increase in the number of MWs saved compared to the model without carbon intensity information
* With perfect knowledge of carbon intensity, the 11am day-ahead, negative reserve setting model would operate at the same risk appetite, but save more MWs compared to the alternative model
* Empirical risk (without carbon intensity): 0.994
* Empirical risk (with carbon intensity): 0.994
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without carbon intensity, lead time <= 10 hours): 150MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with carbon intensity, lead time <= 10 hours): 182MW
	+ 1. 8am day-ahead negative reserve model
* Including carbon intensity for the 8am day-ahead, negative reserve model shows no change in risk performance, but a decrease in the number of MWs saved compared to the model without carbon intensity information
* With perfect knowledge of carbon intensity, the 8am day-ahead, negative reserve setting model would operate at the same risk appetite, but save fewer MWs compared to the alternative model
* Empirical risk (without carbon intensity): 0.994
* Empirical risk (with carbon intensity): 0.994
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without carbon intensity, lead time <= 10 hours): 209MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with carbon intensity, lead time <= 10 hours): 119MW
	1. Difference between national demand forecasts

Full details found in January 2024 progress report.

|  |  |  |  |
| --- | --- | --- | --- |
| Model | **Target** | **Impact on Risk (compared to baseline model)** | **Impact on MW saving per settlement period (compared to baseline model)** |
| 6hr ahead | Positive reserve | Degradation  | 195MW saving (due to worse risk performance) |
| 11am day-ahead | Positive reserve | Candidate features not selected | Candidate features not selected |
| 8am day-ahead | Positive reserve | Candidate features not selected | Candidate features not selected |
| 6hr ahead | Negative reserve | No change | 32MW degradation |
| 11am day-ahead | Negative reserve | Candidate features not selected | Candidate features not selected |
| 8am day-ahead | Negative reserve | Candidate features not selected | Candidate features not selected |

Table : Analysis of the impact of difference between PEF and BMRA national demand forecast data on reserve setting models. For a full list of features selected, see associated progress report.

* + 1. 6hr ahead positive reserve model
* Including difference in national demand forecasts for the 6hr ahead, positive reserve model shows a degradation in risk performance, and as a result of this a significant saving in MWs
* Explicitly providing the model with the difference in national demand forecasts, the 6hr ahead, positive reserve setting model would not meet the desired risk appetite, but as a result show an increased MW saving compared to the alternative model.
* Empirical risk (without system imbalance): 0.006
* Empirical risk (with system imbalance): 0.01
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without system imbalance): 266MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with system imbalance): 461MW
	+ 1. 11am day-ahead positive reserve model
* No difference in national demand features were selected by the feature selection procedure for this experiment, so no results are reported
	+ 1. 8am day-ahead positive reserve model
* No difference in national demand features were selected by the feature selection procedure for this experiment, so no results are reported
	+ 1. 6hr ahead negative reserve model
* Including difference in national demand forecasts for the 6hr ahead, negative reserve model shows no change in risk performance, but a drop in MWs saved. This can be a result of overfitting of the model when provided additional features, and randomness in building the initial trees used to determine feature importance.
* Explicitly providing the model with the difference in national demand forecasts , the 6hr ahead, negative reserve setting model would not have any impact on risk appetite, but would reduce the MW saving compared to the alternative model.
* Empirical risk (without system imbalance): 0.995
* Empirical risk (with system imbalance): 0.995
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without system imbalance): 196MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with system imbalance): 164MW
	+ 1. 11am day-ahead negative reserve model
* No difference in national demand features were selected by the feature selection procedure for this experiment, so no results are reported
	+ 1. 8am day-ahead negative reserve model
* No difference in national demand features were selected by the feature selection procedure for this experiment, so no results are reported
	1. Imbalance on the system

Full details found in January 2024 progress report.

|  |  |  |  |
| --- | --- | --- | --- |
| Model | **Target** | **Impact on Risk (compared to baseline model)** | **Impact on MW saving per settlement period (compared to baseline model)** |
| 6hr ahead | Positive reserve | Negligible degradation  | 148MW saving |
| 11am day-ahead | Positive reserve | Minor improvement | 116MW degradation (due to improvement in risk) |
| 8am day-ahead | Positive reserve | Degradation | 281MW saving (due to degradation in risk) |
| 6hr ahead | Negative reserve | No change | 15MW saving |
| 11am day-ahead | Negative reserve | No change | 83MW saving |
| 8am day-ahead | Negative reserve | No change | No significant change (3MW degradation) |

Table : Analysis of the impact of system imbalance data on reserve setting models. For a full list of features selected, see associated progress report.

* + 1. 6hr ahead positive reserve model
* Including system imbalance for the 6hr ahead, positive reserve model shows a minor degradation in risk performance but a significant saving in MWs compared to the model without system imbalance information
* With perfect knowledge of system imbalance, the 6hr ahead, positive reserve setting model would present significant savings in terms of MWs used for reserve, whilst operating at a very similar risk appetite.
* Empirical risk (without system imbalance): 0.007
* Empirical risk (with system imbalance): 0.006
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without system imbalance): 266MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with system imbalance): 414MW
	+ 1. 11am day-ahead positive reserve model
* Including system imbalance for the 11am day-ahead, positive reserve model shows an improvement in risk performance but as a result saves less MWs compared to the model without system imbalance information
* With perfect knowledge of system imbalance, the 11am day-ahead, positive reserve setting model would operate closer to the target risk appetite, but in doing so saves less MWs compared to the alternative model
* Empirical risk (without system imbalance): 0.011
* Empirical risk (with system imbalance): 0.009
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without system imbalance): 541MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with system imbalance): 425MW
	+ 1. 8am day-ahead positive reserve model
* Including system imbalance for the 8am day-ahead, positive reserve model shows a degradation in risk performance but as a result saves significantly more MWs compared to the model without system imbalance information
* With perfect knowledge of system imbalance, the 8am day-ahead, positive reserve setting model would deviate further from the target risk appetite, but in doing so saves more MWs compared to the alternative model
* Empirical risk (without system imbalance): 0.008
* Empirical risk (with system imbalance): 0.011
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without system imbalance): 355MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with system imbalance): 636MW
	+ 1. 6hr ahead negative reserve model
* Including system imbalance for the 6hr ahead, negative reserve model shows no change in risk performance but results in an increase in the number of MWs saved compared to the model without system imbalance information
* With perfect knowledge of system imbalance, the 6hr ahead, negative reserve setting model would perform at the same risk appetite, whilst saving more MWs compared to the alternative model
* Empirical risk (without system imbalance): 0.995
* Empirical risk (with system imbalance): 0.995
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without system imbalance): 196MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with system imbalance): 211MW
	+ 1. 11am day-ahead negative reserve model
* Including system imbalance for the 11am day-ahead, negative reserve model shows no change in risk performance but an increase in the amount of MWs saved compared to the model without system imbalance information
* With perfect knowledge of system imbalance, the 11am day-ahead, negative reserve setting model would perform at the same risk appetite, whilst saving more MWs compared to the alternative model
* Empirical risk (without system imbalance): 0.994
* Empirical risk (with system imbalance): 0.994
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without system imbalance, lead time <= 10 hours): 150MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with system imbalance, lead time <= 10 hours): 233MW
	+ 1. 8am day-ahead negative reserve model
* Including system imbalance for the 8am day-ahead, negative reserve model shows no change in risk performance and an insignificant change in the amount of MWs saved compared to the model without system imbalance information
* With perfect knowledge of system imbalance, the 8am day-ahead, negative reserve setting model would perform equally in both risk and MW savings when compared to the alternative model
* Empirical risk (without system imbalance): 0.994
* Empirical risk (with system imbalance): 0.994
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without system imbalance, lead time <= 10 hours): 209MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with system imbalance, lead time <= 10 hours): 206MW
	1. Mix of generation on the system (DRS proxy)

Full details found in January 2024 progress report.

|  |  |  |  |
| --- | --- | --- | --- |
| Model | **Target** | **Impact on Risk (compared to baseline model)** | **Impact on MW saving per settlement period (compared to baseline model)** |
| 6hr ahead | Positive reserve | No change | 28MW saving |
| 11am day-ahead | Positive reserve | Improvement | 153MW degradation (due to improvement in risk) |
| 8am day-ahead | Positive reserve | Degradation | 418MW saving (due to degradation in risk) |
| 6hr ahead | Negative reserve | No change | No significant change (5MW saving) |
| 11am day-ahead | Negative reserve | No change | 26MW saving |
| 8am day-ahead | Negative reserve | No change | 13MW degradation  |

Table : Analysis of the impact of generation mix (as determined by a proxy from the DRS database) data on reserve setting models. For a full list of features selected, see associated progress report.

* + 1. 6hr ahead positive reserve model
* Including generation mix (DRS proxy) for the 6hr ahead, positive reserve model shows no change in risk performance and a small increase in the amount of MWs saved compared to the model without generation mix information
* With perfect knowledge of generation mix (DRS proxy), the 6hr ahead, positive reserve setting model would perform equally in risk and better in MW savings when compared to the alternative model
* Empirical risk (without generation mix): 0.006
* Empirical risk (with generation mix): 0.006
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without generation mix, all lead times): 266MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with generation mix, all lead times): 294MW
	+ 1. 11am day-ahead positive reserve model
* Including generation mix (DRS proxy) for the 11am day-ahead, positive reserve model shows a significant improvement in risk performance but a large decrease in the amount of MWs saved compared to the model without generation mix information
* With perfect knowledge of generation mix (DRS proxy), the 11am day-ahead, positive reserve setting model would perform better in risk but, as a result of this, worse in MW savings when compared to the alternative model
* Empirical risk (without generation mix): 0.011
* Empirical risk (with generation mix): 0.005
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without generation mix): 541MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with generation mix): 388MW
	+ 1. 8am day-ahead positive reserve model
* Including generation mix (DRS proxy) for the 8am day-ahead, positive reserve model shows a deterioration in risk performance but a large increase in the amount of MWs saved compared to the model without generation mix information
* With perfect knowledge of generation mix (DRS proxy), the 8am day-ahead, positive reserve setting model would perform significantly worse in risk, but as a result show a larger MW savings when compared to the alternative model
* Empirical risk (without generation mix): 0.008
* Empirical risk (with generation mix): 0.013
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without generation mix): 355MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with generation mix): 773MW
	+ 1. 6hr ahead negative reserve model
* Including generation mix (DRS proxy) for the 6hr ahead, negative reserve model shows no change in risk performance and a small increase in the amount of MWs saved compared to the model without generation mix information
* With perfect knowledge of generation mix (DRS proxy), the 6hr ahead, negative reserve setting model would perform equally in risk and better in MW savings when compared to the alternative model
* Empirical risk (without generation mix): 0.995
* Empirical risk (with generation mix): 0.995
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without generation mix, all lead times): 196MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with generation mix, all lead times): 201MW
	+ 1. 11am day-ahead negative reserve model
* Including generation mix (DRS proxy) for the 11am day-ahead, negative reserve model shows no change in risk performance and an increase in the amount of MWs saved compared to the model without generation mix information
* With perfect knowledge of generation mix (DRS proxy), the 11am day-ahead, negative reserve setting model would perform equally in risk and better in MW savings when compared to the alternative model
* Empirical risk (without generation mix): 0.994
* Empirical risk (with generation mix): 0.994
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without generation mix, lead times <= 10): 150MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with generation mix, lead times <= 10): 176MW
	+ 1. 8am day-ahead negative reserve model
* Including generation mix (DRS proxy) for the 8am day-ahead, negative reserve model shows no change in risk performance and a decrease in the amount of MWs saved compared to the model without generation mix information
* With perfect knowledge of generation mix (DRS proxy), the 8am day-ahead, negative reserve setting model would perform equally in risk and worse in MW savings when compared to the alternative model
* Empirical risk (without generation mix): 0.994
* Empirical risk (with generation mix): 0.994
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without generation mix, lead times <= 10): 209MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with generation mix, lead times <= 10): 196MW
	1. Mix of generation on the system (ESO API)

Full details found in April 2024 progress report.

|  |  |  |  |
| --- | --- | --- | --- |
| Model | **Target** | **Impact on Risk (compared to baseline model)** | **Impact on MW saving per settlement period (compared to baseline model)** |
| 6hr ahead | Positive reserve | Improvement | 56MW degradation (due to improved risk performance) |
| 11am day-ahead | Positive reserve | Improvement | 268MW degradation (due to significantly improved risk performance) |
| 8am day-ahead | Positive reserve | Improvement  | 47MW degradation (due to improved risk performance) |
| 6hr ahead | Negative reserve | No change | 11MW saving |
| 11am day-ahead | Negative reserve | No change | 20MW saving |
| 8am day-ahead | Negative reserve | Candidate features not selected | Candidate features not selected |

Table : Analysis of the impact of generation mix (as determined by the ESO API) data on reserve setting models. For a full list of features selected, see associated progress report.

* + 1. 6hr ahead positive reserve model
* Including generation mix (ESO API) for the 6hr ahead, positive reserve model shows a minor improvement in risk performance but a decrease the amount of MWs saved compared to the model without generation mix information
* With perfect knowledge of generation mix (ESO API), the 6hr ahead, positive reserve setting model would perform better in risk and worse in MW savings when compared to the alternative model
* Empirical risk (without generation mix): 0.006
* Empirical risk (with generation mix): 0.005
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without generation mix, all lead times): 266MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with generation mix, all lead times): 210MW
	+ 1. 11am day-ahead positive reserve model
* Including generation mix (ESO API) for the 11am day-ahead, positive reserve model shows an improvement in risk performance but a decrease the amount of MWs saved compared to the model without generation mix information
* With perfect knowledge of generation mix (ESO API), the 11am day-ahead, positive reserve setting model would perform better in risk and worse in MW savings when compared to the alternative model
* Empirical risk (without generation mix): 0.011
* Empirical risk (with generation mix): 0.006
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without generation mix): 541MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with generation mix): 273MW
	+ 1. 8am day-ahead positive reserve model
* Including generation mix (ESO API) for the 8am day-ahead, positive reserve model shows an improvement in risk performance but a decrease the amount of MWs saved compared to the model without generation mix information
* With perfect knowledge of generation mix (ESO API), the 8am day-ahead, positive reserve setting model would perform better in risk and worse in MW savings when compared to the alternative model
* Empirical risk (without generation mix): 0.008
* Empirical risk (with generation mix): 0.006
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without generation mix): 355MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with generation mix): 308MW
	+ 1. 6hr ahead negative reserve model
* Including generation mix (ESO API) for the 6hr ahead, negative reserve model shows no change in risk performance but a minor increase the amount of MWs saved compared to the model without generation mix information
* With perfect knowledge of generation mix (ESO API), the 6hr ahead, negative reserve setting model would perform equally in risk and better in MW savings when compared to the alternative model
* Empirical risk (without generation mix): 0.995
* Empirical risk (with generation mix): 0.995
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without generation mix, all lead times): 196MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with generation mix, all lead times): 207MW
	+ 1. 11am day-ahead negative reserve model
* Including generation mix (ESO API) for the 11am day-ahead, negative reserve model shows no change in risk performance but an increase the amount of MWs saved compared to the model without generation mix information
* With perfect knowledge of generation mix (ESO API), the 11am day-ahead, negative reserve setting model would perform equally in risk and better in MW savings when compared to the alternative model
* Empirical risk (without generation mix): 0.994
* Empirical risk (with generation mix): 0.994
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without generation mix, lead time <= 10 hours): 150MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with generation mix, lead time <= 10 hours): 170MW
	+ 1. 8am day-ahead negative reserve model
* No generation mix ESO API features were selected by the feature selection procedure for this experiment, so no results are reported
	1. European weather

Full details found in April 2024 progress report.

|  |  |  |  |
| --- | --- | --- | --- |
| Model | **Target** | **Impact on Risk (compared to baseline model)** | **Impact on MW saving per settlement period (compared to baseline model)** |
| 6hr ahead | Positive reserve | Degradation  | 286MW saving (due to degradation in risk) |
| 11am day-ahead | Positive reserve | Improvement | 529MW decrease (due to significant improvement in risk) |
| 8am day-ahead | Positive reserve | Degradation  | 186MW saving (due to degradation in risk) |
| 6hr ahead | Negative reserve | No change | 75MW decrease |
| 11am day-ahead | Negative reserve | No change | 9MW saving |
| 8am day-ahead | Negative reserve | No change | 6MW saving |

Table : Analysis of the impact of European weather actuals data on reserve setting models. For a full list of features selected, see associated progress report.

* + 1. 6hr ahead positive reserve model
* Including EU weather information for the 6hr ahead, positive reserve model shows a significant degradation in risk performance but, as a result of this, an increase in the amount of MWs saved compared to the model without EU weather information
* With perfect knowledge of EU weather, the 6hr ahead, positive reserve setting model would perform significantly worse in risk but better in MW savings when compared to the alternative model
* Empirical risk (without EU weather): 0.006
* Empirical risk (with EU weather): 0.013
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without EU weather, all lead times): 266MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with EU weather, all lead times): 552MW
	+ 1. 11am day-ahead positive reserve model
* Including EU weather information for the 11am day-ahead, positive reserve model shows a significant improvement in risk performance but a decrease the amount of MWs saved compared to the model without EU weather information
* With perfect knowledge of EU weather, the 11am day-ahead, positive reserve setting model would perform better in risk and worse in MW savings when compared to the alternative model
* Empirical risk (without EU weather): 0.011
* Empirical risk (with EU weather): 0.005
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without EU weather, all lead times): 541MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with EU weather, all lead times): 12MW
	+ 1. 8am day-ahead positive reserve model
* Including EU weather information for the 8am day-ahead, positive reserve model shows a decrease in risk performance but an increase the amount of MWs saved compared to the model without EU weather information
* With perfect knowledge of EU weather, the 8am day-ahead, positive reserve setting model would perform worse in risk but better in MW savings when compared to the alternative model
* Empirical risk (without EU weather): 0.008
* Empirical risk (with EU weather): 0.012
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without EU weather, all lead times): 355MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with EU weather, all lead times): 541MW
	+ 1. 6hr ahead negative reserve model
* Including EU weather information for the 6hr ahead, negative reserve model shows no change in risk performance but a decrease the amount of MWs saved compared to the model without EU weather information
* With perfect knowledge of EU weather, the 6hr ahead, negative reserve setting model would perform at the same level of risk but worse in MW savings when compared to the alternative model
* Empirical risk (without EU weather): 0.995
* Empirical risk (with EU weather): 0.995
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without EU weather, all lead times): 196MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with EU weather, all lead times): 121MW
	+ 1. 11am day-ahead negative reserve model
* Including EU weather information for the 11am day-ahead, negative reserve model shows no change in risk performance and a minor increase in the amount of MWs saved compared to the model without EU weather information
* With perfect knowledge of EU weather, the 11am day-ahead, negative reserve setting model would perform at the same level of risk and slightly better in MW savings when compared to the alternative model
* Empirical risk (without EU weather): 0.994
* Empirical risk (with EU weather): 0.994
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without EU weather, lead times <= 10 hours): 150MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with EU weather, lead times <= 10 hours): 159MW
	+ 1. 8am day-ahead negative reserve model
* Including EU weather information for the 8am day-ahead, negative reserve model shows no change in risk performance but a slight increase the amount of MWs saved compared to the model without EU weather information
* With perfect knowledge of EU weather, the 8am day-ahead, negative reserve setting model would perform at the same level of risk and slightly better in MW savings when compared to the alternative model
* Empirical risk (without EU weather): 0.994
* Empirical risk (with EU weather): 0.994
* Average MW saving (using a dynamic model compared to a static one) per settlement period (without EU weather, lead times <= 10 hours): 209MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (with EU weather, lead times <= 10 hours): 215MW
	+ 1. Manual hyperparameter selection

The 6hr ahead and 8am day-ahead positive reserve models have a significant decrease in risk performance when provided with EU weather data. As previously noted, not all hyperparameters are automatically tuned during model fitting, and two in particular are manually specified: the number of trees in the ensemble, and the learning rates to apply. When we run the EU weather experiment, we introduce many additional candidate features, and as we expand the size of the candidate feature set, it may be more important to recalibrate these manually selected hyper-parameters. As an example, we re-ran experiments with EU weather for the two positive reserve models noted, but we reduced the learning rates and number of trees – which should combat overfitting as the candidate feature set has been vastly expanded. The results for doing this are shown below.

|  |  |  |  |
| --- | --- | --- | --- |
| Model | **Target** | **Impact on Risk (compared to baseline model)** | **Impact on MW saving per settlement period (compared to baseline model)** |
| 6hr ahead | Positive reserve | No change | 174MW decrease |
| 8am day-ahead | Positive reserve | Improvement (moves to a risk of 0.005 compared to the baseline model with 0.008, targeting a risk of 0.003) | 270MW decrease (due to improvement in risk) |

Table : Analysis of the impact of European weather actuals data on reserve setting models, when the number of trees has been halved (50 instead of 100) and the learning rate has been reduced by a factor of 10 (0.02 instead of 0.2). For a full list of features selected, see associated progress report.

From the analysis above, it is clear in future experiments that as the pool of candidate features is vastly expanded, the manually specified hyperparameters can have a significant impact on the risk performance of the model. Whilst we still do not see significant benefits of including EU weather data in the model, we do see that a large candidate feature set size can easily lead to poor risk performance if the number of trees and learning rates are not adjusted to account for this. Note that in the negative reserve models, we already use fewer trees and a lower learning rate, as this was observed to be optimal for that class of models in an earlier phase of DRS, whereas more freedom to fit the data gave better positive reserve models in the same phase.

* 1. OCF PVNet (without probabilistic features)

Full details found in April 2024 progress report.

|  |  |  |  |
| --- | --- | --- | --- |
| Model | **Target** | **Impact on Risk (compared to baseline model)** | **Impact on MW saving per settlement period (compared to baseline model)** |
| 6hr ahead | Positive reserve | Degradation  | 286MW saving (due to degradation in risk) |
| 11am day-ahead | Positive reserve | Improvement | 198MW decrease (due to improvement in risk) |
| 8am day-ahead | Positive reserve | Candidate features not selected | Candidate features not selected |
| 6hr ahead | Negative reserve | Candidate features not selected | Candidate features not selected |
| 11am day-ahead | Negative reserve | No change | 7MW decrease |
| 8am day-ahead | Negative reserve | No change | 82MW decrease |

Table : Analysis of the OCF PVNet data (without probabilistic features) on reserve setting models. For a full list of features selected, see associated progress report. Note that we understand these forecasts are a blend between the PVNet model and a gradient boosted tree model, depending on lead time.

* + 1. 6hr ahead positive reserve model
* Including OCF non-probabilistic solar features for the 6hr ahead, positive reserve model shows a degradation in risk performance and as a result, an improvement in the amount of MWs saved compared to the model using ESO’s solar features
* With OCF non-probabilistic solar features, the 6hr ahead, positive reserve setting model would perform worse in risk and better in MW savings when compared to the alternative model
* Empirical risk (ESO solar features): 0.006
* Empirical risk (OCF non-probabilistic solar features): 0.013
* Average MW saving (using a dynamic model compared to a static one) per settlement period (ESO solar features, all lead times): 266MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (OCF non-probabilistic solar features, all lead times): 552MW
	+ 1. 11am day-ahead positive reserve model
* A Including OCF non-probabilistic solar features for the 11am day-ahead, positive reserve model shows an improvement in risk performance and a degradation in the amount of MWs saved compared to the model using ESO’s solar features
* With OCF non-probabilistic solar features, the 11am day-ahead, positive reserve setting model would perform better in risk but worse in MW savings when compared to the alternative model
* Empirical risk (ESO solar features): 0.011
* Empirical risk (OCF non-probabilistic solar features): 0.008
* Average MW saving (using a dynamic model compared to a static one) per settlement period (ESO solar features): 541MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (OCF non-probabilistic solar features): 343MW
	+ 1. 8am day-ahead positive reserve model
* No OCF features were selected by the feature selection procedure for this experiment, so no results are reported
	+ 1. 6hr ahead negative reserve model
* No OCF features were selected by the feature selection procedure for this experiment, so no results are reported
	+ 1. 11am day-ahead negative reserve model
* Including OCF non-probabilistic solar features for the 11am day-ahead, negative reserve model shows no difference in risk performance and a slight degradation in the amount of MWs saved compared to the model using ESO’s solar features (considering lead times less than 10)
* With OCF non-probabilistic solar features, the 11am day-ahead, negative reserve setting model would perform at the same level of risk and slightly worse in MW savings when compared to the alternative model (considering lead times less than 10)
* Empirical risk (ESO solar features): 0.994
* Empirical risk (OCF non-probabilistic solar features): 0.994
* Average MW saving (using a dynamic model compared to a static one) per settlement period (ESO solar features, lead times <= 10): 150MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (OCF non-probabilistic solar features, lead times <= 10): 143MW
	+ 1. 8am day-ahead negative reserve model
* Including OCF non-probabilistic solar features for the 8am day-ahead, negative reserve model shows no difference in risk performance and a degradation in the amount of MWs saved compared to the model using ESO’s solar features (considering lead times less than 10)
* With OCF non-probabilistic solar features, the 8am day-ahead, negative reserve setting model would perform at the same level of risk and worse in MW savings when compared to the alternative model (considering lead times less than 10)
* Empirical risk (ESO solar features): 0.994
* Empirical risk (OCF non-probabilistic solar features): 0.994
* Average MW saving (using a dynamic model compared to a static one) per settlement period (ESO solar features, lead times <= 10): 209MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (OCF non-probabilistic solar features, lead times <= 10): 127MW
	1. OCF PVNet (with probabilistic features)

Full details found in April 2024 progress report.

|  |  |  |  |
| --- | --- | --- | --- |
| Model | **Target** | **Impact on Risk (compared to baseline model)** | **Impact on MW saving per settlement period (compared to baseline model)** |
| 6hr ahead | Positive reserve | Slight degradation  | 85MW saving  |
| 11am day-ahead | Positive reserve | Slight degradation | 98MW saving |
| 8am day-ahead | Positive reserve | Candidate features not selected | Candidate features not selected |
| 6hr ahead | Negative reserve | No change | 35MW degradation  |
| 11am day-ahead | Negative reserve | No change | 9MW degradation |
| 8am day-ahead | Negative reserve | No change | 51MW degradation |

Table : Analysis of the OCF PVNet data (with probabilistic features) on reserve setting models. For a full list of features selected, see associated progress report. Note that we understand these forecasts are a blend between the PVNet model and a gradient boosted tree model, depending on lead time.

* + 1. 6hr ahead positive reserve model
* Including OCF probabilistic solar features for the 6hr ahead, positive reserve model shows a slight degradation in risk performance and an increase in the amount of MWs saved compared to the model using ESO’s solar features
* With OCF’s probabilistic solar features, the 6hr ahead, positive reserve setting model would perform at a slightly higher level of risk and with an increase in MW savings when compared to the alternative model
* Empirical risk (ESO solar features): 0.006
* Empirical risk (OCF probabilistic solar features): 0.008
* Average MW saving (using a dynamic model compared to a static one) per settlement period (ESO solar features, all lead times): 266MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (OCF probabilistic solar features, all lead times): 351MW
	+ 1. 11am day-ahead positive reserve model
* Including OCF probabilistic solar features for the 11am day-ahead, positive reserve model shows a slight degradation in risk performance and an increase in the amount of MWs saved compared to the model using ESO’s solar features
* With OCF’s probabilistic solar features, the 11am day-ahead, positive reserve setting model would perform at a slightly higher level of risk and with an increase in MW savings when compared to the alternative model
* Empirical risk (ESO solar features): 0.011
* Empirical risk (OCF probabilistic solar features): 0.013
* Average MW saving (using a dynamic model compared to a static one) per settlement period (ESO solar features, all lead times): 541MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (OCF probabilistic solar features, all lead times): 639MW
	+ 1. 8am day-ahead positive reserve model
* No OCF features were selected by the feature selection procedure for this experiment, so no results are reported
	+ 1. 6hr ahead negative reserve model
* Including OCF probabilistic solar features for the 6hr ahead, negative reserve model shows no difference in risk performance and a degradation in the amount of MWs saved compared to the model using ESO’s solar features
* With OCF’s probabilistic solar features, the 6hr ahead, positive reserve setting model would perform the same level of risk and with a degradation in MW savings when compared to the alternative model
* Empirical risk (ESO solar features): 0.995
* Empirical risk (OCF probabilistic solar features): 0.995
* Average MW saving (using a dynamic model compared to a static one) per settlement period (ESO solar features, all lead times): 196MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (OCF probabilistic solar features, all lead times): 161MW
	+ 1. 11am day-ahead negative reserve model
* Including OCF probabilistic solar features for the 11am day-ahead, negative reserve model shows no difference in risk performance and a degradation in the amount of MWs saved compared to the model using ESO’s solar features (considering lead times less than 10)
* With OCF’s probabilistic solar features, the 11am day-ahead, positive reserve setting model would perform the same level of risk and with a degradation in MW savings when compared to the alternative model (considering lead times less than 10)
* Empirical risk (ESO solar features): 0.994
* Empirical risk (OCF probabilistic solar features): 0.994
* Average MW saving (using a dynamic model compared to a static one) per settlement period (ESO solar features, lead times <= 10): 150MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (OCF probabilistic solar features, lead times <= 10): 141MW
	+ 1. 8am day-ahead negative reserve model
* Including OCF probabilistic solar features for the 8am day-ahead, negative reserve model shows no difference in risk performance and a degradation in the amount of MWs saved compared to the model using ESO’s solar features (considering lead times less than 10)
* With OCF’s probabilistic solar features, the 6hr ahead, positive reserve setting model would perform at the same level of risk and with a degradation in MW savings when compared to the alternative model (considering lead times less than 10)
* Empirical risk (ESO solar features): 0.994
* Empirical risk (OCF probabilistic solar features): 0.994
* Average MW saving (using a dynamic model compared to a static one) per settlement period (ESO solar features, lead times <= 10): 209MW
* Average MW saving (using a dynamic model compared to a static one) per settlement period (OCF probabilistic solar features, lead times <= 10): 158MW
1. Discussion of solar features in reserve setting

One aspect we consider during these experiments is the impact solar data has on reserve setting. We aggregate results from different experiments involving solar features for each reserve setting model in this section.

* 1. Global feature importance for the reserve setting models

Before discussing the impact of solar features on the reserve setting models, we first highlight that when looking at global feature importance for the models, solar is not one of the most significant features present. Far more dominant drivers of reserve requirement are temporal (time of day, month and week), wind (speed, embedded wind load factor & variation in wind) and sometimes air temperature as well. Therefore, changes to the solar inputs to the model would not be expected to vastly shift the performance unless the existing ESO features are very poor in capturing the true expected solar state of the grid. We showcase an example of the global feature importance of all variables in the 11am day-ahead positive reserve model in Figure 1. This is the model that was trained using the solar features ESO currently have available for use internally, so is a sensible ‘benchmark’.



Figure : Global feature importance for the 11am day-ahead positive reserve setting model. Time of day and month are the most important features for this model. Average wind speed forecasts in different regions of the UK appear as the 3rd and 4th most important features. Average solar radiance for a specific region of GB appears as the 8th most important feature (solar\_radiance\_mean\_group\_5\_forecast), and average solar radiance for another region of GB appears as the 14th most important feature (solar\_radiance\_mean\_group\_3\_forecast).

* 1. 6hr ahead positive reserve model

|  |  |  |
| --- | --- | --- |
| Model setup | **Impact on Risk (target is 0.003, existing ESO model operates empirically at ~0.006)** | **Impact on MW saving per settlement period (compared to baseline model)** |
| No national or regional solar features  | **0.009 (+0.003 from baseline)** | **141MW saving**  |
| No national embedded solar features, but the model does have existing ESO regional solar irradiance features | **0.010 (+0.004 from baseline)** | **199MW saving**  |
| Existing ESO national embedded PV forecasts (from PEF) & existing ESO regional solar irradiance features | **0.006** | **[This is the baseline we compare against]** |
| PV Live & existing ESO regional solar irradiance features | **0.007 (+0.001 from baseline)** | **64MW saving**  |
| OCF point forecasts & existing ESO regional solar irradiance features | **Model did not select any OCF point forecast features** | **Model did not select any OCF point forecast features** |
| OCF PVNet (without probabilistic) forecasts & existing ESO regional solar irradiance features | **0.013 (+0.007 from baseline)** | **286MW saving** |
| OCF PVNet (with probabilistic) forecasts & existing ESO regional solar irradiance features | **0.008 (+0.002 from baseline)** | **85MW saving** |

Table : Analysis of the impact of solar features on the 6hr ahead positive reserve setting model.

When removing solar features from the 6hr ahead positive reserve setting model, the quality of the model clearly decreases compared to the baseline. This is shown with the significant degradation of risk performance in Table 13. Perfect solar outturn knowledge through PV Live data shows a slight degradation in the risk, less significant degradation than for the non-solar cases. The OCF point forecasts were not selected by the model fitting procedure, which may indicate they are not close enough to the true, underlying PV live values they model to be of similar use to the reserve setting model. Of all forecasts considered, the OCF PVNet (with probabilistic) appear to balance risk performance with MW savings (gaining a MW savings without significantly compromising risk), noting that the PV Live data uses actuals in place of forecasts, so cannot be considered for practical use.

* 1. 11am day-ahead positive reserve model

|  |  |  |
| --- | --- | --- |
| Model setup | **Impact on Risk (target is 0.003, existing ESO model operates empirically at ~0.007)** | **Impact on MW saving per settlement period (compared to baseline model)** |
| No national or regional solar features  | **0.012 (+0.001 from baseline)** | **81MW saving**  |
| No national embedded solar features, but the model does have existing ESO regional solar irradiance features | **0.013 (+0.002 from baseline)** | **50MW saving**  |
| Existing ESO national embedded PV forecasts (from PEF) & existing ESO regional solar irradiance features | **0.011** | **[This is the baseline we compare against]** |
| PV Live & existing ESO regional solar irradiance features | **0.014 (+0.003 from baseline)** | **24MW saving**  |
| OCF point forecasts & existing ESO regional solar irradiance features | **Model did not select any OCF point forecast features** | **Model did not select any OCF point forecast features** |
| OCF PVNet (without probabilistic) forecasts & existing ESO regional solar irradiance features | **0.008 (-0.003 from baseline)** | **198MW decrease** |
| OCF PVNet (with probabilistic) forecasts & existing ESO regional solar irradiance features | **0.013 (+0.002 from baseline)** | **98MW saving** |

Table : Analysis of the impact of solar features on the 11am day-ahead positive reserve setting model.

As seen and discussed in Figure 1, solar features are not of much importance to the 11am model, and in-fact that model in particular does not select the existing ESO national solar forecast as a feature. Therefore, when removing or altering national solar forecasts, we are in a sense adding or removing noise from the model fitting process. Contracting the size of the candidate feature set, as occurs when the baseline model without any solar features is considered, may require finer tuning of the manually specified hyperparameters (number of trees and learning rates) to get the same performance of the model with a larger feature set, even if some of those features are not important for modelling. However, when considering the OCF PVNet (with probabilistic) forecasts, we see the same risk performance as when removing national embedded solar features, but a greater MW savings. This suggests that there is some value in having uncertainty in solar forecasts represented in the model, rather than removing them entirely.

* 1. 8am day-ahead positive reserve model

|  |  |  |
| --- | --- | --- |
| Model setup | **Impact on Risk (target is 0.003, existing ESO model operates empirically at ~0.007)** | **Impact on MW saving per settlement period (compared to baseline model)** |
| No national or regional solar features  | **0.013 (+0.005 from baseline)** | **319MW saving**  |
| No national embedded solar features, but the model does have existing ESO regional solar irradiance features | **0.011 (+0.003 from baseline)** | **207MW saving**  |
| Existing ESO national embedded PV forecasts (from PEF) & existing ESO regional solar irradiance features | **0.008** | **[This is the baseline we compare against]** |
| PV Live & existing ESO regional solar irradiance features | **Model did not select any PV Live features** | **Model did not select any PV Live features** |
| OCF point forecasts & existing ESO regional solar irradiance features | **0.011 (+0.003 from baseline)** | **133MW saving**  |
| OCF PVNet (without probabilistic) forecasts & existing ESO regional solar irradiance features | **Model did not select any OCF features** | **Model did not select any OCF features** |
| OCF PVNet (with probabilistic) forecasts & existing ESO regional solar irradiance features | **Model did not select any OCF features** | **Model did not select any OCF features** |

Table : Analysis of the impact of solar features on the 8am day-ahead positive reserve setting model.

For the 8am day-ahead positive reserve setting model, we see the models appear to get worse when solar features are removed, shown by the degradation in risk compared to the baseline. The same behaviour is observed when we replace the ESO solar forecasts from PEF with OCF point forecasts. Interestingly, the model does not select PV live features when they are supplied in place of PEF features. This may be an artefact of our feature selection process. We determine feature importance by building an initial model and considering as more important features that are present in more trees in the model. Therefore, when multiple related features are included, the importance of each single feature can be reduced, as the model can use either of two related inputs to get the same performance. Therefore, it may be that providing this model with both the load factor from PV live, as-well as the raw generation values, reduces the relative importance of the feature sufficiently to not have it selected in the fitting process.

* 1. 6hr ahead negative reserve model

|  |  |  |
| --- | --- | --- |
| Model setup | **Impact on Risk (target is 0.997, existing ESO model operates empirically at ~0.997)** | **Impact on MW saving per settlement period (compared to baseline model)** |
| No national or regional solar features  | **0.995 (no change from baseline)** | **18MW saving**  |
| No national embedded solar features, but the model does have existing ESO regional solar irradiance features | **0.995 (no change from baseline)** | **35MW decrease**  |
| Existing ESO national embedded PV forecasts (from PEF) & existing ESO regional solar irradiance features | **0.995** | **[This is the baseline we compare against]** |
| PV Live & existing ESO regional solar irradiance features | **0.995 (no change from baseline)** | **10MW decrease**  |
| OCF point forecasts & existing ESO regional solar irradiance features | **0.995 (no change from baseline)** | **12MW saving**  |
| OCF PVNet (without probabilistic) forecasts & existing ESO regional solar irradiance features | **Model did not select any OCF features** | **Model did not select any OCF features** |
| OCF PVNet (with probabilistic) forecasts & existing ESO regional solar irradiance features | **0.995 (no change from baseline)** | **35MW decrease** |

Table : Analysis of the impact of solar features on the 6hr ahead negative reserve setting model.

The 6hr ahead negative reserve model, as with other negative reserve models, shows consistent risk performance as we vary the solar features. However, the magnitude of changes to MW savings across these experiments appear simply as noise rather than a significant saving, and as a result we conclude that there is little impact of improving solar forecasts for the 6hr ahead negative reserve model. Throughout the experiments discussed in this report, we have seen how difficult it is to find significant improvements to the 6hr ahead negative reserve setting model, with many experiments showing only minor changes in MW savings.

* 1. 11am day-ahead negative reserve model

|  |  |  |
| --- | --- | --- |
| Model setup | **Impact on Risk (target is 0.997, existing ESO model operates empirically at ~0.994)** | **Impact on MW saving per settlement period (compared to baseline model)** |
| No national or regional solar features  | **0.994 (no change from baseline)** | **53MW saving**  |
| No national embedded solar features, but the model does have existing ESO regional solar irradiance features | **0.994 (no change from baseline)** | **41MW saving** |
| Existing ESO national embedded PV forecasts (from PEF) & existing ESO regional solar irradiance features | **0.994** | **[This is the baseline we compare against]** |
| PV Live & existing ESO regional solar irradiance features | **0.994 (no change from baseline)** | **99MW saving**  |
| OCF point forecasts & existing ESO regional solar irradiance features | **0.994 (no change from baseline)** | **4MW saving** |
| OCF PVNet (without probabilistic) forecasts & existing ESO regional solar irradiance features | **0.994 (no change from baseline)** | **7MW decrease** |
| OCF PVNet (with probabilistic) forecasts & existing ESO regional solar irradiance features | **0.994 (no change from baseline)** | **9MW decrease** |

Table : Analysis of the impact of solar features on the 11am day-ahead negative reserve setting model.

For the 11am day-ahead negative reserve setting model, we see that changes to the candidate feature set do not impact the risk performance. When removing the solar features, we see a 41-53MW saving depending on the ones removed, which would suggest the model is doing a better job at modelling the relationships in the data without solar features. Recall that several variables relate highly to solar, so in removing a solar feature, the model could conceivably change its internal usage of air temperature, wind, time of day and season to account for this removal. When exact solar knowledge is added to the model through PV live, we do see a large MW saving of 99MW, which again may be down to how the model is able to use the features available to it to understand the relationships present. Using the OCF point forecasts in-place of the ESO PEF solar forecast appears to offer no significant change, improvement or degradation, in relation to MW savings, and this is also true for the OCF PVNet forecasts (both with and without probabilistic information).

* 1. 8am day-ahead negative reserve model

|  |  |  |
| --- | --- | --- |
| Model setup | **Impact on Risk (target is 0.997, existing ESO model operates empirically at ~0.994)** | **Impact on MW saving per settlement period (compared to baseline model)** |
| No national or regional solar features  | **0.994 (no change from baseline)** | **29MW decrease**  |
| No national embedded solar features, but the model does have existing ESO regional solar irradiance features | **0.994 (no change from baseline)** | **14MW decrease**  |
| Existing ESO national embedded PV forecasts (from PEF) & existing ESO regional solar irradiance features | **0.994** | **[This is the baseline we compare against]** |
| PV Live & existing ESO regional solar irradiance features | **Model did not select any PV Live features** | **Model did not select any PV Live features** |
| OCF point forecasts & existing ESO regional solar irradiance features | **0.994 (no change from baseline)** | **52MW decrease**  |
| OCF PVNet (without probabilistic) forecasts & existing ESO regional solar irradiance features | **0.994 (no change from baseline)** | **82MW decrease** |
| OCF PVNet (with probabilistic) forecasts & existing ESO regional solar irradiance features | **0.994 (no change from baseline)** | **51MW decrease** |

Table : Analysis of the impact of solar features on the 8am day-ahead negative reserve setting model.

For the 8am day-ahead negative reserve setting model, we see similar results to the 11am day ahead model. Risk is not impacted by changes in the solar data provided, but any changes to MW savings are not improvements in the model. As before, recall that several variables relate highly to solar, so in removing a solar feature, the model could conceivably change its internal usage of air temperature, wind, time of day and season to account for this removal. It is impossible to fully diagnose the internal behaviour of the complex models we use. We can instead say that modest MW changes can be made with alterations to how solar features are provided to this model – but note these changes are decreases in the MWs saved, so not a candidate for future investigation.