THE IMPACT OF FORECASTING ACCURACY ON THE ECONOMIC PERFORMANCE OF FLEXIBILITY PROVISION

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ABSTRACT

Aggregation by Virtual Power Plants (VPP) to provide flexibility to distribution and transmission networks is seen as an important element in the transition to Net-zero. This paper presents work carried out in the SIES 2022 ERA-Net project, which is investigating in detail the possible provision of flexibility by different technologies but thorough a lens of different business models. Forecasting is an important element of a VPP's functionality and to its commercial success. Forecasting errors are reviewed using real project data and used to simulate an optimisation of project assets using both actual and forecast data, allowing a quantification of the effects of forecasting errors on VPP performance.

INTRODUCTION

Virtual Power Plants (VPP) will form an important element in the development of a future low carbon power market, as they will ease the interactions of system operators with thousands of potential customers. Exactly how these sources of flexibility will be managed and the economic impact on the players is still unclear. The challenge of employing flexibility in generation, consumption and storage in the context of a VPP depends on the appropriate optimization of market access, assets and an understanding of the constraints on the wider distribution system. The Engineering Technology Centre in Central Scotland (ETC) is a partner in the SIES 2022 ERA-Net consortium which has been set up to deliver a technology demonstrator system to manage energy pools using VPP software and to investigate how this VPP could operate using a variety of assets in a realistic setting. ETC has interests in two energy pools which are available for immediate deployment in the project:

- ETC's own premises and the wider Scottish Enterprise Technology Park energy infrastructure.
- A test area at the Myres Hill wind turbine site.

The sites include both electrical and thermal loads that can be used for flexibility as well as other consumers in the area. Future DSO/TSO[1] flexibility markets will require the efficient operation of aggregators to ensure the safe and economic operation of the system. An important element of this will be the ability to forecast power output, imbalance volumes and market prices. Although forecasting of wholesale day ahead prices is well documented and reasonably accurate, the same cannot be said of flexibility markets. Initial work suggests that forecasting flexibility prices accurately, will be difficult. In addition, those markets are still actively evolving so historical data to train such models is lacking. Using the pilot demonstrator plant introduced above, the effect on the operation of the VPP at this site is shown using different forecasting methodologies, both from a technical and economic point of view. It will be shown that the inaccuracies in the forecast methodologies presents challenges to VPP operations. Using real data collected from the project over that last 6 months, forecasting errors using selected forecasting algorithms are reviewed and analysed. The data from this analysis is used in a VPP simulation to ascertain the effect of forecasting errors on the economics of a case study example.

ROUTES TO MARKET:BMRS

There are many routes to market available to a potential VPP owner. At its simplest owners could just sell to a retailer or some large consortium via what is essentially a fixed price contract. In this work we use Elexon's 2022 BMRS (Balancing Mechanism Reporting Service) imbalance market prices [1, 2] as a surrogate for a future flexibility market. These are used as an input to the simulation and for an analysis of forecast errors (Figure 1).

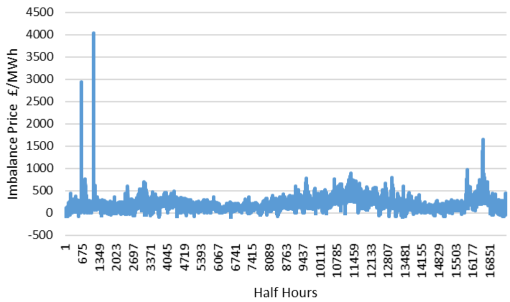

Figure 1: BMRS 2022 prices

[1] Distribution/Transmission System Operator

FORECASTING ACCURACY OF KEY INPUTS

Weather e.g. wind, is typically used to drive power output (kW) forecasts. Along with prices forecasts, they form important inputs into optimisation or decision algorithms which are then used to schedule assets to improve the revenue potential of owners. The following section reviews the operating experience of the VPP demonstrator at ETC premises, using data collected over the last 6 months.

Wind Forecasting Actuals vs Forecast

Machine learning based algorithms are now being used to forecast wind output. Catboost [3] is considered to be one of the best, but not the fastest, of the gradient boosting class of machine learning algorithms. Others, like LightGBM [4], XGboost [5] or a neural network architecture could also be used. Figure *2* shows the output of the forecast against actual active power readings from the turbine at the ETC demonstrator site using a Catboost algorithm. Data is shown for different time horizons.

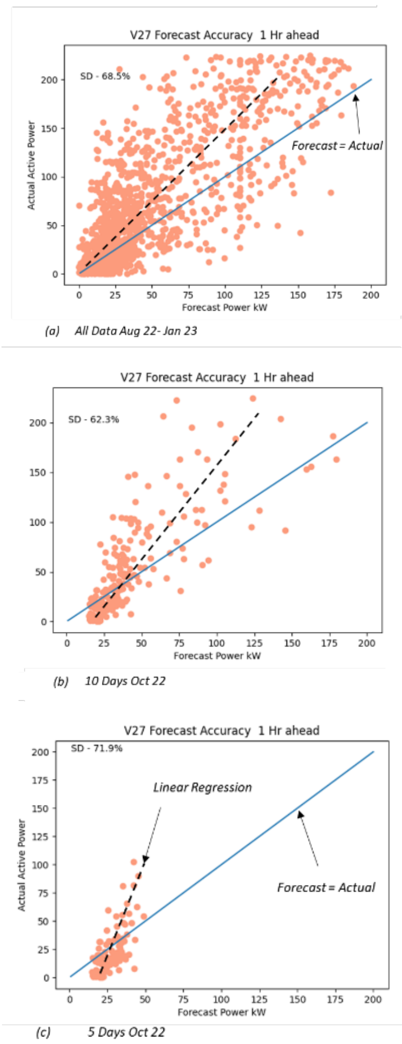

Figure 2: Myres Hill wind turbine data (actual vs forecast) using CatBoost algorithm

Four hours ahead, forecasts look somewhat similar to those shown in Figure 2, but, as expected, longer forecast time horizons get worse. It is more difficult to predict the wind over longer time horizons. Note that shorter period forecasts appear to produce less errors in forecast values, than using wider time horizons. In addition, using the actual forecast results in a poorer performance than using the black dashed regression line which somewhat corrects the forecast value to a tighter view of the actuals. Note these are initial models and the project team is in the process of improving them using, for example, up to date wind turbine measurements.

Logistic Equation Regression

Using the same data as presented above, an analysis using logistic curves has been carried out on the actual power vs wind data. The logistic curve somewhat mirrors the manufacturer's power output curve. The curve has been fitted to the wind power data using a genetic algorithm curve fitting approach and the results are shown in Figure *3* below. Comparison of the fitted curve with the manufacturer's data shows that there is some departure from the fitted curve at certain points highlighting the need to use a data driven approach to forecasting.

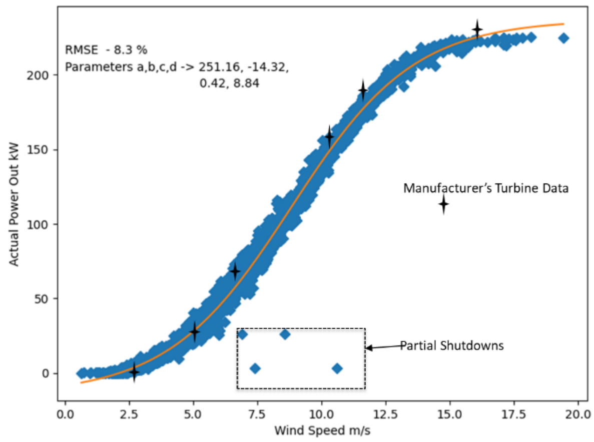

Figure 3: Myres Hill wind turbine curve fit – logistic equation

Figure 4 uses the fitted logistic equation to forecast power output using wind data and plots the forecast against actual real power output. The wind data itself has a forecast error and is included in this figure. Short-term wind forecasts appear to be relatively good, and are not shown for brevity. It is clear that forecasting with a logistic curve provides better results than CatBoost algorithm initially used. Of course using a combination of the two forecasting techniques might yield improvements over any one method, as we might expect one method to perform better than others under certain conditions.

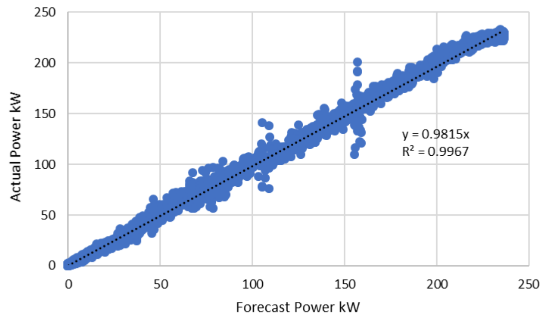

Figure 4: Myres Hill wind turbine data (actual vs forecast) – Logistic equation

Many academic papers use one normal distribution for the whole ranges of outputs. Errors across the forecast power spectrum, however, are markedly different (Figure 5). Note use of the absolute errors rather than percentage produces a more realistic output.

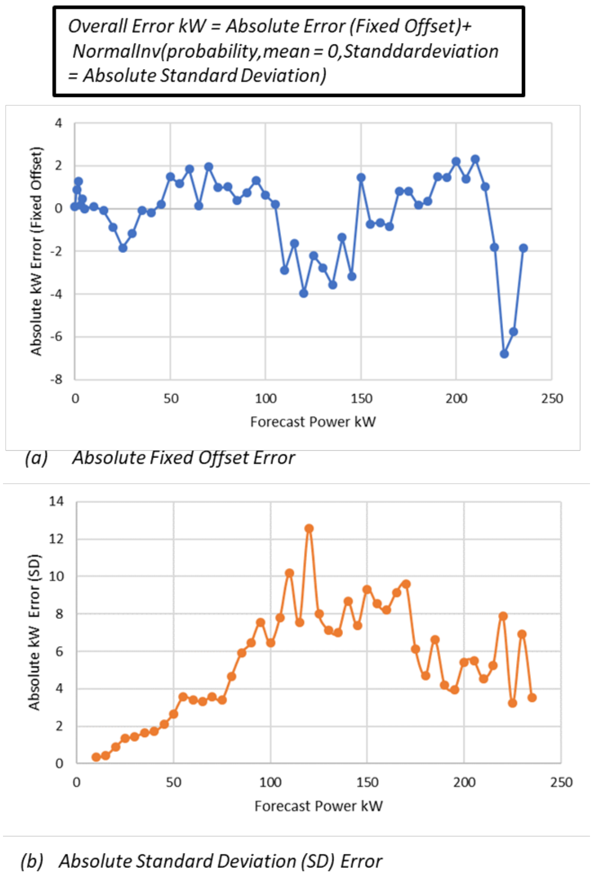

Figure 5: Absolute errors (kW) – Logistic power forecast equation

In the simulation that follows, only the logistic forecasting methodology is used for power output. Absolute error terms (an offset and standard deviation) shown in Figure 5 are used as inputs in the simulation that follows and are dependent upon forecast power.

Price Forecasting Actuals vs Forecast

Price forecasting of imbalance or flexibility prices is proving difficult [6]. This is not surprising as the many underlying drivers of prices in this market or flexibility markets in general are difficult to forecast.

This leads one to consider probabilistic approaches as well as risk management as an option to hedge downside risk. This paper will not focus on any specific algorithm, or consider the impact of risk management, but will use a multi-linear regression equation to represent the BMRS forecast. Using historical BMRS data from Elexon, ForecastPro software [7] has been used to formulate a BMRS forecasting model. This model has an $R^2 = 0.69$ and RMSE of £35/MWh. Forecast absolute errors prices can be as high £200 - £400/MWh. This is consistent with others work in forecasting BMRS prices. The results from this analysis are shown in Figure 6.

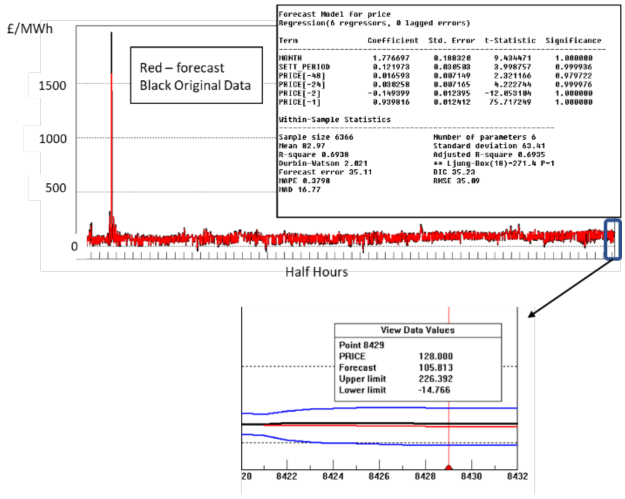

Figure 6: BMRS forecast using ForecastPro software

Forecast BMRS prices are formulated from a variety of lagged prices and variables associated with the settlement period (1-48 half hours) and the month (1-12). Figure 7 compares the forecast from ForecastPro with actual values. Errors for lower and high prices are less pronounced.

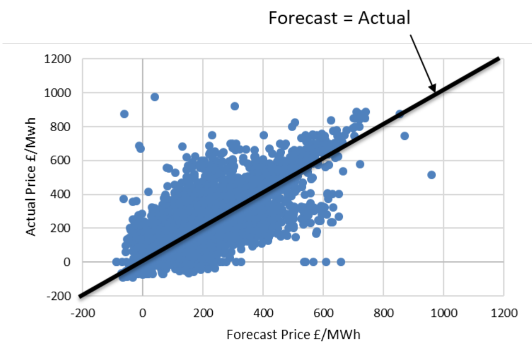

Figure 7: BMRS actual vs forecast

ILLUSTRATED CASE STUDY

The project has created a number of use cases on which to test out various metrics. One is used here to illustrate the effect of forecasting errors on the economic performance of the current pilot VPP project at ETC. Other algorithms could have been used. E.g. fixed order control or simple heuristics.

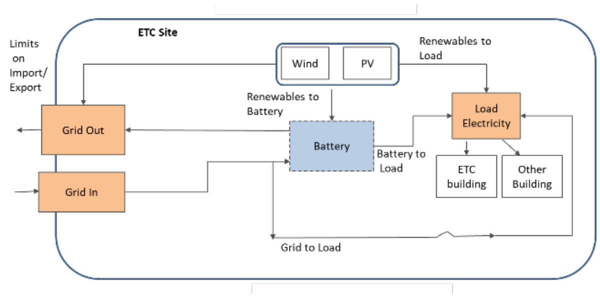

Figure 8: Illustrated case study

The ETC demonstrator site has many different assets including a flow battery, a 178kWh Delta Li-ion Battery charger, a heat pump, thermal store, and variable electrical loads. For this illustrative case study we are going to concentrate on the interactions with the Li-Ion battery, the small Wind and PV units and the loads at two industrial buildings (one is associated with ETC) (see Figure *8*). The wind (10kW) and PV (12 kW) units can be used to supply the electrical loads (min: 1.5kW max: 59 kw, with additional spikes of 80kW), charge the battery or can be exported to the grid. Imports can also be used to charge the battery and supply the loads. Lastly, the battery can be used to supply the loads or export to the grid.
The optimiser output is used by the VPP to schedule real assets. A further issue here is that the optimiser scheduler output will be sent to the assets at fixed time intervals e.g. half hour, 15 mins and so on. In practice. loads, wind output etc. will vary at inter time step, so errors in performance could be introduced, but it is ignored in this paper.

DATA DRIVEN SIMULATION

The simulation methodology is presented in Figure 9.

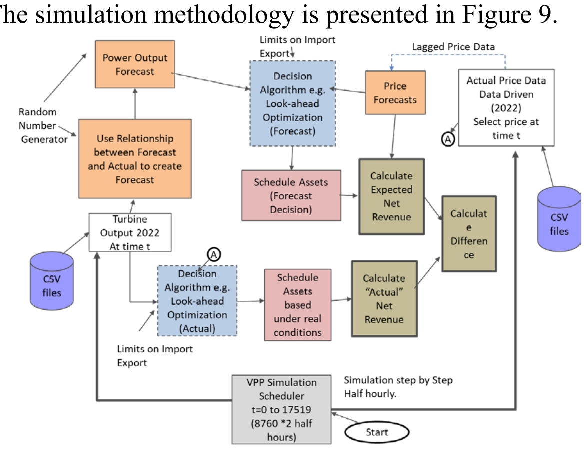

Figure 9: Simulation methodology

It uses a Pyomo [8] based forward-looking optimisation method (model predictive control), to optimise a wind turbine, a solar module, and a battery to meet electrical loads at ETC and a neighbouring premises. The model looks to maximize net revenues (Exports – Imports) and is based on the work in reference [9, 10].
The simulation methodology uses actual vs forecast data to look at how an optimiser would perform using the actuals or forecast data. The forecast data is used to generate schedules for battery action, which are then assumed fixed for the next half-hour. Prices, actual loads, and renewable inputs would be different from forecasts, so imports and exports would change. The difference in net revenue (outturn vs the perfect forecast) represents the economic dis-benefit of the forecasts on the simulation output. The base case uses actual error profiles as discussed in the various sections above. Additional cases using larger or smaller errors are included

CASE STUDY RESULTS

Case study results are presented in Figure 10, Table 1 and Figure *11*. The first figure shows how the net optimiser actions for the battery action in kW changes between forecasts and that of using a perfect forecast for the base case. Table 1 and Figure *11* shows how yearly net revenues change when forecasts, perfect foresight and the actual response (outturn) are considered. Equation 1 below defines the calculation for yearly net revenues in all these cases.

$$Net\,\mathrm{Re}venues = \sum_{t=0}^{17519} (BMRSprice_t * (\mathrm{Export\_kW}_t - Import\_\mathrm{kW}_t) * 0.5 \qquad 1$$

Note the system buy and sell price in the BMRS are the same. The base case assumes actual renewables at ETC (wind and solar) with the price and wind error profiles discussed above. Other cases change the magnitude of the price and wind errors using a scalar multiplication factor.

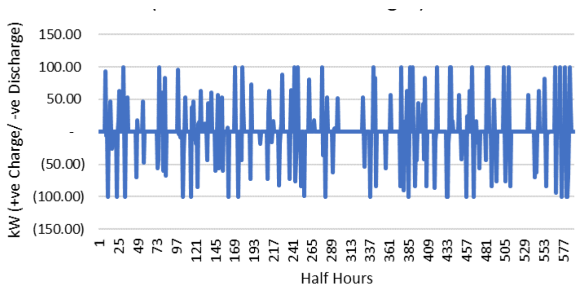

Figure 10: Case study results – Change in battery actions (forecast –perfect foresight)

Case	Forecast £/Year	Perfect Foresight £/Year	Outturn £/Year	Dis-benefit £	%
Base Case	3,594	2,925	2,585	-340	-12%
Error x 0.5	3,879	2,925	2,179	-746	-26%
Error x 1.5	5,171	2,925	1,094	-1,831	-63%
Error x2	5,971	2,925	333	-2,592	-89%

Table 1: Case study results - yearly revenues with different error profiles

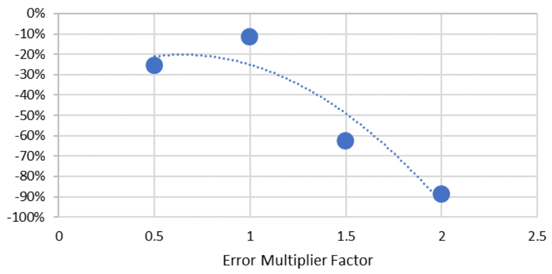

Figure 11: Case study results – Change in net revenue over perfect forecast case

Unsurprisingly, revenues are affected more with an increase in the error in forecasting. The base case forecasting methodology is producing net revenues that are around 12% lower than an ideal case using perfect foresight. Forecast errors results in incorrect actions, but in this example are counteracted by the errors in the price forecast, i.e. they are negatively correlated. However, this will not always be the case and will depend on algorithm and market selected.

CONCLUSIONS AND FUTURE WORK

Using data collected from the SIES 2022 ERA-Net consortium's VPP project based at ETC's East Kilbride demonstrator, an analysis of wind power and BMRS forecast errors has been performed.

A model of future BMRS prices has also been developed and used to compare forecasts with actuals.

The results from the analysis on wind and price forecasting have been utilised to simulate the impact on an optimisation of some of the ETC assets. Results indicate that:

- The current methodology results in revenues some 12% lower than a perfect forecast.
- Larger errors in absolute terms on wind and price inputs could result in errors >50%, which may prove unacceptable to a commercial aggregator.

Future work is proposed to include the effect of risk management or use of probabilistic approaches on the economic performance. The framework proposed can be extended to:

- Include other optimisation algorithms and heuristics.
- To investigate the potential impact of inter-time period errors; that is errors introduced by changes between schedule set point changes.
- To investigate the effect of errors with different asset combinations.

The ultimate aim would be to derive a heuristic that provides insights into the impact forecast errors on economic performance and provide correction signposts or signals to improve performance for different markets and different asset combinations.

Acknowledgments

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