Applied Energy 256 (2019) 113973

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Optimization of a multiple-scale renewable energy-based virtual power plant in the UK

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HIGHLIGHTS

- A comparative analysis for various scales virtual power plant model is presented.
- The virtual power plant consists of scattered wind farms and one biomass plant.
- The day-ahead and balancing markets are considered.
- Results showing significant profit increase are analyzed.

ARTICLE INFO

Keywords:
Virtual power plant
Wind energy
Biomass energy
Electricity markets
Energy trading

ABSTRACT

Commercial Virtual Power Plants (CVPPs) have recently emerged as one of the most promising solutions for enabling intermittent renewable energy generation sources to efficiently trade the energy they generate in the electricity market. In this study, we develop several optimization and forecasting methods, and apply them to model the operation of multiple renewable generators across Scotland, trading energy as a single CVPP. The aim of the techniques developed is to optimize the scheduling of the CVPP, such as to maximize revenues and reduce the penalties resulting from forecasting errors, while considering operational and market constraints, such as variable costs, ramping rates, start-up costs, day-ahead and imbalance prices. The practical application is based on a case study of operational renewable energy plants in Scotland, and optimizes the CVPP operation for 3 months in winter and summer of 2017, respectively. Renewable generation output, day-ahead prices and imbalance prices are obtained from historical data for the same year. The numerical results show a profit increase of around 12% for the CVPP compared to standalone operation of renewable plants. This increase is observed for different market and imbalance settlement strategies.

1. Introduction

1.1. Motivation & approach

The need for renewable energy is increasing at a fast pace, in order to decrease the reliance on conventional fossil fuel-based power plants, due to recent environmental guidelines and policies, such as the first large scale legally binding agreement reached at the Paris climate conference in December 2015, where 195 countries agreed to reduce greenhouse emissions and act to mitigate climate change [1]. Similarly, the UK has set ambitious targets for clean energy systems. At least 15% of UK's energy consumption is planned to be covered from Renewable Energy Sources (RES) by 2020 [2], but only 9.3% of the target was achieved in 2016 [3].

To achieve the 2020 target, it is necessary to ensure a reliable penetration from a mix of RES generation, such as wind and solar, which

Abbreviations: ANN, Artificial Neural Network; ARIMA, Autoregressive Integrated Moving Average; ARMA, Autoregressive Moving Average; BESP, Break-Even Selling Price; BPP, Biomass Power Plant; CHP, Combined Heat and Power; CVPP, Commercial Virtual Power Plant; DCF, Discounted Cash Flow; DER, Distributed Energy Resource; EEX, European Energy Exchange; ENTSOE, European Network of Transmission System Operators for Electricity; EPEX, European Power Exchange; ESS, Energy Storage System; IEA, International Energy Agency; LCOE, Levelized Cost of Energy; MILP, Mixed Integer Linear Programming; NWP, Numerical Weather Prediction; O&M, Operation & Maintenance; PEM, Point Estimate Method; RES, Renewable Energy Source; RMSE, Root-Mean Square Error; TSO, Transmission System operator; TVPP, Technical Virtual Power Plant; VPP, Virtual Power Plant; WF, Wind Farm

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https://doi.org/10.1016/j.apenergy.2019.113973
Received 19 April 2019; Received in revised form 13 September 2019; Accepted 8 October 2019
Available online 17 October 2019
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are highly intermittent in nature and dependent on weather conditions. For example, wind power generation is stochastic and difficult to predict. In particular, wind power is proportional to the wind speed, which is a function of various weather parameters, such as relative humidity, air temperature, atmospheric pressure and precipitation [4]. Accurate forecasting for wind power generation is necessary to avoid imbalances in the electricity grid, which may impose cost penalties on Wind Farm (WF) operators [5]. Similarly, solar generation also depends on weather patterns and needs to be accurately forecasted.

Virtual Power Plants (VPPs) have recently emerged as one of the most promising concepts to reduce the financial and technical risks presented by such intermittent energy sources [6]. A VPP consists of multiple Distributed Energy Resource (DER) units such as Renewable Energy Sources (RES), Energy Storage Systems (ESS), Combined Heat and Power (CHP) units or other technologies that act as a single generating unit [7]. Existing literature identifies two main types of VPPs; Technical Virtual Power Plants (TVPPs) [8] and Commercial Virtual Power Plant (CVPPs) [7]. A TVPP combines different DERs from the same geographic location in order to produce an aggregate output that is similar to a conventional power plant. Hence, TVPPs facilitate power system management and interface with the operation of the electricity grid. A CVPP can perform across geographic scales by commercially aggregating multiple DERs with the objective to maximize their profits.

In microgrid operation a group of various energy generators is used to serve a specific area either in coordination or separately from the main electricity grid. By comparison, VPPs do not have this limitation and may contribute to electricity grid balancing [9]. VPPs are also typically used to aggregate geographically distributed and intermittent energy sources, in order to reduce risk and uncertainty in electricity production, as the accuracy of forecasts and errors is improved when the distance between aggregated units is increased [10]. The latter forms the main focus of this work and more specifically the optimization of the energy management for a CVPP. The following section elaborates on related research works in the field.

1.2. Literature review

A literature review revealed different optimization algorithms for VPPs across multiple configurations. A probabilistic day-ahead optimization algorithm is presented in [8], used for the aggregation of multiple renewable energy units, CHP units, electrical and thermal storage. The VPP participates in the day-ahead and spinning reserve market. Forecasting scenarios used the Point Estimate Method (PEM) to simulate wind output and prices uncertainty. The study found that most of the time the VPP was buying from the spinning reserve market and the CHP ramping capability could have been explored to cover shortages of supply.

In [11], a cluster of multiple CHPs was proposed and a new optimization method based on Mixed Integer Linear Programming (MILP) was developed that aimed to increase the revenues of the CHP cluster compared to individual operations. CHP units were scheduled to operate when the day-ahead prices are low and shut down when prices are high. The results showed a 10% reduction in operating costs; however the study did not explore the ramping capabilities of the CHP units nor the potential for generating profits in the real-time or balancing market.

A proposed two-stage optimization algorithm to schedule a microgrid consisting of multiple DERs [12] was proved to be powerful. It is, however, purely optimizing based on the plants generation costs and not considering the market prices. A stochastic programming based VPP model [13] schedules its output according to day-ahead prices, production and storage costs constraints. The equiprobable operation scenarios used in the objective function tend to only be efficient if the output and prices are already known.

In [14] a combination of aggregation of wind and hydro storage units was considered. A risk constrained method was utilised in the day-ahead market. Wind power uncertainty was accounted for by assuming multiple generation scenarios with Monte Carlo simulation. The hydro units followed recursive actions in real-time operation, in order to preserve to the total scheduled power and prevent any deviation from the schedule submitted to the day-ahead market. A constrained payoff function accounts for the imbalance penalty and hydro units generation costs. The results showed that coordinated operation between wind and hydro units yielded reduced imbalance and associated penalty risks, however, the optimization method resulted in curtailment of wind power in real-time operation, to avoid the imposition of penalties. Curtailment is when wind power generation is wasted in order to avoid penalties from power imbalances as in [14], or most typically to avoid congestion or network constraints [15].

Using the same payoff concept, a coordinated operation of hydro, wind and natural gas units was considered in [16] with the objective to minimize operating costs of the natural gas and hydro units and reduce imbalance penalties. The optimization method developed in [16] achieved the objective with increased payoffs and reduced financial risks.

Robu et al. [17] used multi-agent technology to provide efficient payment mechanisms and incentives for cooperative formation of multiple DERs in CVPPs. The study achieved VPP formation by reducing the joint forecasting error of the participating DERs.

The in-depth review of relevant research works revealed considerable knowledge gaps in the existing literature in terms of new methods for:

1. Market participation and optimization trading of VPPs when day-ahead prices are unknown and potentially volatile.
2. Modelling the VPP trading, based on large-scale data and real-world case studies.
3. Consideration of a dispatchable (but still low emission) generator, such as a Biomass Power Plant (BPP), integrated with DERs in the same VPP.

This work seeks to address these knowledge gaps by advancing the state of the art. The main contributions of this paper can be summarized as follows:

– To our knowledge, this paper is one of the first to assume a continuous loop simulation for the duration of a year and a two-stage optimization, for the day-ahead market and for real-time operation. Existing literature - of which we are aware – uses probabilistic modelling techniques, whereas this work provides an applied computational/trading model for the control management of dispatchable plants in real-time markets that compensates for intermittent RES deviation from the scheduled energy plan.
– The work advances the state of the art by extending the optimization framework to include the day-ahead and real-time prices, while also incorporating uncertainty through an Autoregressive Moving Average (ARMA) model. Simulation results are based on a specific duration timeline and assume unknown values for the day-ahead renewable energy output and market prices, hence, representing a more realistic approach.
– The proposed VPP is considered to be the first large scale CVPP to be implemented in Scotland, one of the regions with the highest renewable resources in the UK and currently investing in such advanced energy management technologies.
– Realistic simulation assumptions were considered in this work by restricting the amount of excess power sold to the balancing market.
– Finally, this paper is one of the first, to our knowledge, to combine CVPP optimization and uncertainty modelling with multiple integration scenarios analysis for various renewable plants and separation distances that allow for an evident and realistic comparison between profits achieved by aggregated plants and individual operation.

2. Problem background and methodology

2.1. Organization of the electricity market

The electricity market consists primarily of generators, suppliers, non-physical traders and the Transmission System Operator, represented in the UK by the National Grid [18]. Generators are power plants owners, who sell their generated power to energy suppliers (retailers) via future bilateral contracts or in the wholesale energy market. Energy suppliers are responsible of supplying electricity to consumers in the retail market. The TSO is responsible for the real-time matching of electricity supply to the demand, in order to balance the system and avoid power outages. Non-physical traders act as intermediate merchants between generators and suppliers and trade electricity for profit without actually generating any power or satisfying any demand.

The energy exchange in the UK is mainly covered by the European Power Exchange (EPEX), which is part of EEX (European Energy Exchange), based in Germany [19]. Every day generators submit their forecasted energy output to EPEX along with the corresponding price they are willing to accept for the following day, starting from 00:00 (UK Time zone) and for 24 h with a time step of 30 min. Similarly, suppliers submit their forecasted energy demand volume for every half an hour and the corresponding price they are willing to pay to serve such demand. The bid submission closes at 12:00 (UK Time zone); this is called the day-ahead market [20,21]. After gate closure, market clearing prices (day-ahead prices) are announced based on the supply and demand curves intersection for each trading interval or settlement period. A trading interval of 30 min represents 48 settlement periods each day. Generator bids are based on forecasted and scheduled energy to be generated in the following day, and once the generation period starts at 00:00 am, generators are committed and expected to deliver the contracted volumes, at each settlement period and at the cleared day-ahead market price. If the generator fails to deliver the contracted volume, it is subjected to a penalty for the imbalance created (negative imbalance) and needs to purchase additional energy at the balancing (real-time) market to compensate for the shortage created. Similarly, if more than the contracted volume is generated (positive imbalance), the surplus is sold in the balancing market at the real-time market selling price [22].

It is obvious that energy trading in such markets represents a financial risk for highly intermittent renewable energy sources such as wind generators, since the energy scheduled and bids from wind farm operators rely heavily on accurate wind forecasts [23]. Forecasting errors may result in lower actual production than the submitted bid, and hence imply costs for the operator stemming from the need to participate in the balancing market. Accurate forecasts of the output energy are therefore of great importance along with back-up of intermittent sources, in order to satisfy contractual arrangements and deliver the contracted volume. Wind farms' trading strategy needs to carefully consider potential profit gains or losses originating from the imbalance and deviation from the day-ahead scheduled power.

Imbalance settlement differs as per each country's energy market regulation and policy. The basis of all policies is penalizing the generator for shortages and negative deviation of the scheduled power. Broadly speaking, the system buys energy if the output is lower than scheduled (up-regulation) and sells energy if there is an excess of production (down-regulation). The imbalance pricing policies have different types. Single pricing is applied using either the up regulation or down regulation price for the imbalance [24]. Dual pricing is using two different values for the up and down regulation and most likely a higher price for the up-regulation than the price of the down-regulation [25]. The positive (surplus) and negative imbalance (shortage) terms used in the current paper are consistent with definitions provided by the UK administrator of the Balancing and Settlement Code, ELEXON [26]. In the UK, the buying price is higher than the selling price which makes surplus sales in the balancing market less profitable than the day-ahead market.

A different option for RES generators is trading in the Intra-day market. The Intra-day market works particularly well for RES generators, especially wind farms, as it allows them to adjust the bidding strategy every 4 h i.e. closer to real-time generation. Wind farms operators can benefit from this market as wind forecast errors are generally lower for shorter time horizon forecasts (4–8 h) and allow them to repeatedly revise their bidding [27]. In the following section, different techniques for wind forecasting are discussed.

2.2. Wind forecasting

Two main methods for wind forecasting are Numerical Weather Prediction (NWP) models [28], which use measurements of weather parameters, such as by wind turbines anemometers, and statistical methods [29], which can be as simple as the *persistence model* or as complicated as Artificial Neural Network (ANN) techniques.

The persistence model is arguably the simplest method of wind forecasting. Broadly speaking, the method assumes that the wind speed or power after a certain time horizon is equal to its value at the current time. The prediction of wind speed and subsequent conversion to power output tends to be more accurate than directly predicting the power output. The persistence model yields higher errors for long term forecasts (i.e. 12 h) and lower errors for shorter time horizons, such as forecasting for a few hours ahead (i.e. 2 h). The persistence model is often used as a benchmark case or references for comparison against the accuracy any other forecasting model [29].

It is obvious that the forecasting horizon is one of the most important factors affecting the accuracy of the forecast. Wind power is primarily a function of wind speed, which in turn is a function of weather parameters such as humidity, atmospheric pressure and temperature. The behaviour of weather is more accurately predicted for shorter time horizons.

ANNs represent a machine learning solution concept able to recognize data patterns and predict future trends by getting fed with multiple inputs. ANN is a very powerful method especially as it is able to correlate inputs and outputs, which are hard to compute, and is able to approximate non-linear functions. However, good performance indicates a large requirement of input parameters. In [30], ANN was used to forecast wind power output over a period of 24 h. The results yielded a mean error of 7.26%, significantly lower than the persistence model, which if used in the same application, yielded a mean error of 19.05%.

The most classical and conventional statistical methods of forecasting are called Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA) [31]. A detailed explanation for statistical time series analysis is given in [32].The application of ARMA(p,q) or ARIMA(p,d,q) is based on the concept of stationarity, which can be defined as the trend of a time series to exhibit the same behaviour at multiple snapshots. The models consist of different parameters, parameter p represents the Autoregressive (AR) part, d the integral part and q the Moving Average part.

ARMA(p,q) is accurate for stationary series and can be described by the following general expression:

$$y_t = \delta + \sum_{i=1}^{p} \varphi_i y_{t-i} + \varepsilon_t - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{1}$$

where δ, $\varphi_i$are the model coefficients, $\varepsilon_t$represents white noise (uncorrelated random values).

ARIMA(p,d,q) includes an additional integral term d (sum of differences) [33], which is equal to the difference between time steps $(y_t - y_{t-1})$ if d = 1, and $\{(y_t - y_{t-1}) - (y_{t-1} - y_{t-2})\}$ if d = 2, and so on. The difference between time steps is performed to transform the time series to stationary.

Both models use historical data to recognize data patterns and build the regression formula which is used to forecast future times series data. The basic steps of forecasting with ARMA or ARIMA are listed below

[34]:

1. Identification of the model orders (p,q) or (p,d,q)
2. Estimation of the model coefficients
3. Diagnosis check for model validation and forecasting use

In this work, seasonal ARMA models with different orders were used for each wind farm and day-ahead price forecasting. Seasonality was assumed due to the tendency of wind speed patterns to be repeated every week (explained in detail in the following section). To estimate the order of the model, the Akaike Information Criterion (AIC) [35] was introduced. Estimated forecasting models can be evaluated with AIC and the model with minimum AIC value was taken as the best fit [32].

2.3. Model assumptions

In this work, a model of a CVPP was assumed consisting of different wind farms (WFs) and a biomass power plant (BPP). For simplicity, the following assumptions were made in our model:

– VPP trading was not assumed to affect market prices. In reality, both generators and suppliers bid for the expected generation and consumption, respectively. Bids are then integrated on the trading platform as a supply-demand curve, and then the equilibrium prices are obtained by the intersections and for each trading interval [18]. The effect of the VPP to the wholesale energy market and consequent price change was assumed to be small enough to be negligible.
– Annual fixed Operation and Maintenance (O&M) costs for wind farms and the BPP are neglected in the objective function, since their effects are negligible on the evaluation results for the profitability of the VPP.
– O&M annual cost of the BPP was assumed not to affect dispatch decisions. In this work, BPP's O&M cost is only used to extract the relation of cost per (MWh) to the load factor. The BPP is only operated when prices exceed variable (fuel + carbon penalty) costs.
– BPP's variable costs include both fuel and carbon penalty costs. Dealing separately with these costs requires more information about the actual CO2 emissions per MWh than was available at the time of study.
– VPP forecasting was performed on the summation of the actual power outputs of wind farms, not on the wind speeds.
– The BPP operates with a value equal to the wind energy imbalance in the balancing market regardless of the operating cost. No optimization was considered for trading in the balancing market.

The BPP operation is optimized with mixed integer linear programming (MILP), a typical linear programming optimization method, where decision variables are assumed to be integers [11]. A defined percentage (60% in Scenario 1 and 70% in Scenario 2) of the BPP nominal power is scheduled in the day-ahead market, only when the forecasted day-ahead prices are higher than its O&M and start-up costs. The remainder is used to tackle wind power schedule deviations in the balancing market. It is assumed that the BPP compensates for the imbalances occurring at any time (t) after (t + 0.5) (30 min lag), based on the wind persistence model concept, which is suitable for short-term forecasting.

Historical data for day-ahead and imbalance prices are obtained from ENTSOE (European Network of Transmission System Operators for Electricity) transparency platform [36], and are available for every half an hour. Actual electricity generation from wind is collected from Elexon's balancing market reports [37].

Energy scheduling and optimization takes place in the day-ahead market. In the balancing market the VPP aims to commit to its schedule derived and minimize any negative imbalances. The simulations performed were based on historical data for 3 months in winter (January, February, and March) and in summer for (July, August, and September) of 2017.

Bidding of forecasted wind energy output and biomass is submitted at 12:00. As the bidding strategy refers to the 24 h from 00:00 until the following day 00:00 (48 settlement periods), forecasting should also include an additional 12 h, between 12:00 pm and 00:00 for continuity. For imbalance calculations, these 12 h are removed, and only previous day forecasts are considered. Hence, the forecasting horizon needs to be equal to 36 h, which can be categorized as long-term forecast. As a result, ANN or ARMA methods would yield lower forecasting error than the persistence method.

The method selected in this work was an ARMA(p,q) model used to forecast wind power output for 36 h ahead starting from 12:00 pm every day. Data used for training and estimation of model parameters and ARMA coefficients are based on data for one month (December 2016), before the simulation period. Model orders p and q were estimated by trial and error and for each combination of parameters, the AIC is obtained. The model yielding the minimum value of AIC is chosen, as most suitable ARMA coefficient estimation. Matlab's "Econometric Modeler" toolbox [38] was used assuming a seasonal ARMA model (4 seasons). The same process was repeated for day-ahead prices, which need to be forecasted, in order to decide on the optimal operation of the BPP.

The VPP under consideration consists of four wind farms: Todleburn (27.6 MW), Minsca (36.8 MW), Dalswinton (30 MW), and Edinbane (41.4 MW), and one dedicated biomass plant: Stevens Croft (44 MW), all located in Scotland. Three wind farms are widely separated with more than 500 km distance between, as shown in Fig. 1. Dalswinton and Minsca have closer proximity and are only 25 km apart. This geographical separation is required to avoid high correlation between wind farm outputs, which might be helpful, such that if one farm experiences a negative imbalance, this could be compensated by the positive imbalance provided by a different farm.

Stevens Croft is a 44 MW and 6.5 MW_{th} medium-sized dedicated biomass power plant owned by E.ON UK, first installed in 2007 [39]. It primarily uses soft wood as fuel for the boiler to produce high pressure (137 bar) steam, which is required to then operate a Siemens SST-800turbine [40]. According to a detailed plant economic analysis presented in [41], the project capital cost was 93 million GBP including capital and commissioning costs. The annual O&M costs form a total of 4.5% of the capital cost. From the capital cost and assumed Discounted Cash Flow (DCF) factors of 5% and 10%, a Break-Even Selling Price (BESP) curve versus the load factor is obtained. From the BESP curve, fuel price (wood chips) in GBP/MWh and the calculated payback period (equal to 13 years for a 10% DCF factor), the operational cost in GBP/MWh can be estimated by reverse analysis (see also Fig. 2) of the International Energy Agency (IEA) standard Levelized Cost of Energy (LCOE) formula [42]:

$$LCOE = \frac{\sum [(Capital_t + O\&M_t + Fuel_t + Carbon_t + D_t).(1 + DCF)^{-t}]}{\sum MWh.\,(1 + DCF)^{-t}} \tag{2}$$

MWh	Amount of energy generated in year t
O&M	Operation and maintenance expenditures in year t
$Fuel_t$	Fuel cost at year t
$Carbon_t$	Carbon penalty cost in year t
$(1 + DCF)^{-t}$	Discount rate factor at year t
D_t	Decommissioning and waste management annual costs in year t

The technical minimum operating power of the plant was considered to be 40% of the nominal power (17.6 MW), similar to the minimum operating range of a lignite-fired power plant. The up/down ramping limits were set to 8.8 MW/h (i.e. equal to 20% of the full load/minimum load ratio, as a conservative value) [43].

The BPP start-up was estimated from hot start generic values for a

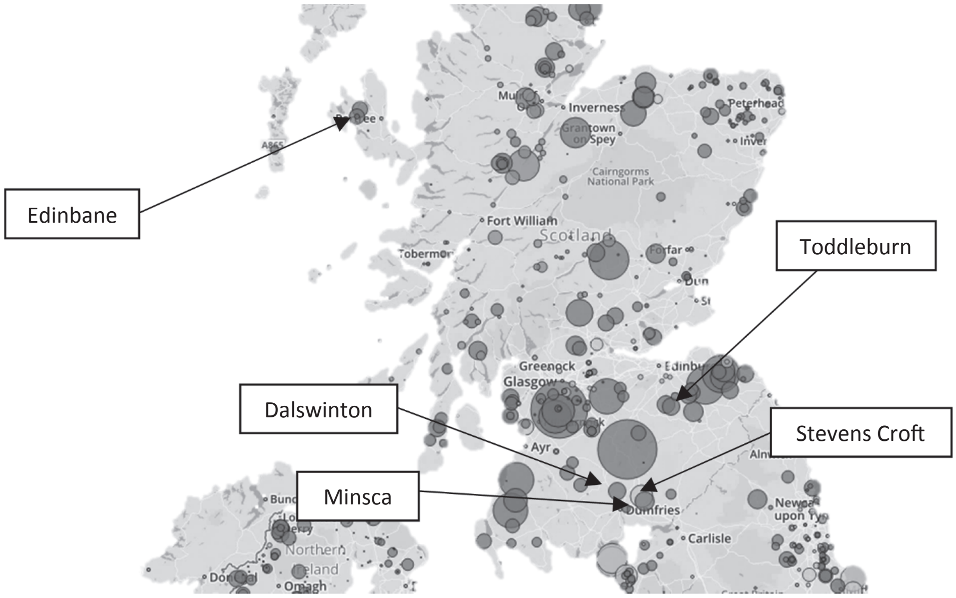

Fig. 1. VPP wind farms and biomass power plant locations – Scotland map [50].

supercritical coal plant (having the highest values) [44]. The start-up cost was calculated from the following parameters:

- Required thermal input was assumed equal to10.1 MMBTU/MW × 44 MW = 444.4 MMBTU = 468.6 MJ [44]
- Lowest heat value (for as-received willow) was estimated at12.92 MJ/kg
- Required input fuel quantity for start-up was assumed equal to 36.26 kg
- Willow price was set at 6 GBP/kg [45]
- Fuel price for start-up was estimated at 6 × 36.26 = 217.56 GBP
- Other start-up costs were estimated at 4.64 GBP/MW (5.81 $/MW) × 44 (MW) = 204.16 GBP [44] (conversion from USD to GBP was based on the exchange rate on January 2017 [46] i.e. the start of the simulation)
- Finally, the total start-up cost was estimated at 422 GBP

For simplification, minimum up and down times are not considered in the optimization, although for more accurate simulation the plant should not be off for more than 8 h to avoid the possibility of a costly cold start [43].

3. Optimization model

The objective of the optimization is to maximize the profit of the VPP assuming that bidding is submitted for the day-ahead market, while also considering uncertainties and imbalance costs. The decision variables of the optimization aim to determine the generation of the BPP under several operational constraints, such as the ramping limit, day-ahead forecasted prices and minimum up or down times.

Nomenclature

α_t^{DA}	Day-ahead Prices at time t (GBP/MWh)
α_t^{DAf}	Forecasted day-ahead prices at time t (GBP/MWh)
α_t^{IMB}	Imbalance prices at time t (GBP/MWh)
P_t^{SchBPP}	BPP output power to be scheduled at time t (MW)
P_t^{ImbBPP}	BPP output power to compensate the wind imbalance at time t (MW)
P^{BPP}	BPP Nominal power
P_{min}^{BPP}	BPP technical minimum power
P_t^{WFn}	

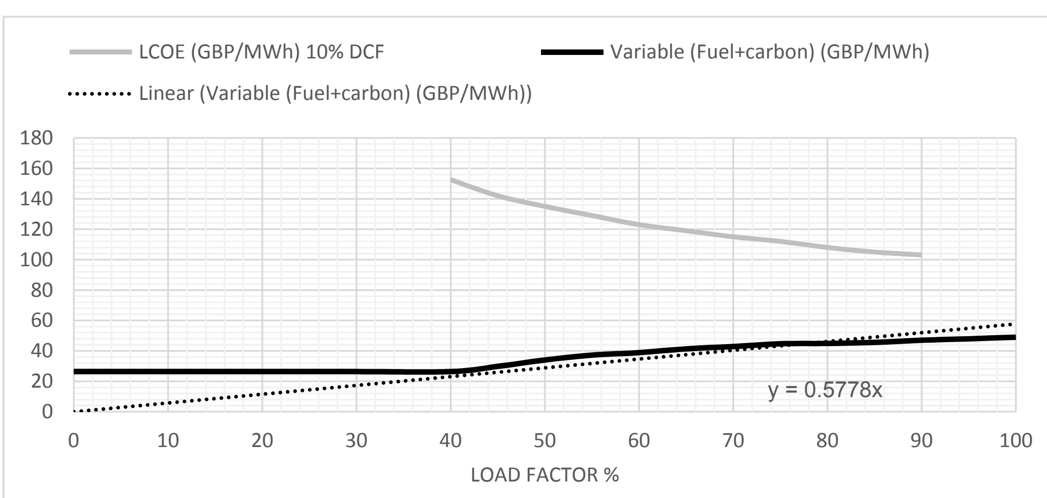

Fig. 2. Variable operating costs of Stevens Croft inferred from LCOE (BESP from 40% to 90% assumed from [41]). The cost function is linearized with zero intercept, in order to achieve a linear optimization.

	Wind farm actual output power (MW) (n = 1 for Toddleburn, 2 for Minisca, 3 for Dalswinton and 4 for Edinbane)
$P_t^{SchWF_n}$	Forecasted (Scheduled) wind farm output power (MW)
StC_t	BPP Start-up cost (GBP)
C_t^{OP}	BPP operation cost (GBP/MWh)
r_t	BPP ramp rate at time t (MW/hr)
u_t	Binary integer (1,0), activates or cancels the StC variable if the BPP starts at time t
y_t	Binary integer (1,0), activates or cancels the C variable if the BPP starts at time t
f^{Sch}	Factor [0,1], assign a percentage for BPP to be scheduled in the day-ahead market, the remaining portion is left to operate in the balancing market

The formal representation of the optimization process is given by the MILP formulation and the maximization of the objective function or VPP profit as follows:

Maximize:

$$Profit = \alpha_t^{DA} ix\left(\sum_1^N P_t^{SchWF_n} + P_t^{SchBPP}\right) + \alpha_t^{IMB} \left(P_t^{ImbBPP} + \sum_1^N P_t^{WF_n} - \sum_1^N P_t^{SchWF_n}\right) - C_t^{OP} x (P_t^{SchBPP} + P_t^{ImbBPP}) - y_t xStC \tag{3}$$

subjected to the following constraints (see Table 1 for a description of each constraint):

$$C_t^{OP} = 57.78x\left(\frac{P_t^{SchBPP} + P_t^{ImbBPP}}{P^{BPP}}\right) \tag{4}$$

$$57.78x\left(\frac{P_t^{SchBPP}}{P^{BPP}}\right) \le \alpha_t^{DAf} \tag{5}$$

$$u_t \in \{0, 1\} \tag{6}$$

$$y_t \in \{0, 1\} \tag{7}$$

$$u_t - u_{t-1} \le y_t \tag{8}$$

$$u_t x P_{min}^{BPP} \le P_t^{SchBPP} \le u_t x f^{Sch} x P^{BPP} \tag{9}$$

$$u_t x P_{min}^{BPP} \le P_t^{ImbBPP} + P_t^{SchBPP} \le u_t x P^{BPP} \tag{10}$$

$$P_t^{ImbBPP} = \sum_1^N P_{t-0.5}^{WF_n} - \sum_1^N P_{t-0.5}^{SchWF_n} \tag{11}$$

$$-r_t \le P_t^{ImbBPP} - P_{t-1}^{ImbBPP} \le r_t \tag{12}$$

The imbalance settlement policy in the UK is based on single pricing policy. The VPP is penalized for the negative imbalance at a price equal to the surplus selling price. Assumption on UK energy prices were based on data collection from ENTSOE [36].

Optimization was performed using Matlab. The forecasting model was obtained by the Econometrics toolbox. Simulations were executed at a Lenovo laptop with Quad core 2.6 GHz processor and 16 GB RAM. The simulation for each season took around 4 min to solve and the results were analyzed using Microsoft Excel.

The simulation is based on 2 cases and 13 scenarios as shown in Table 2. Scenarios consider different combinations of asset participation in the VPP, while cases represent different assumptions with respect to the priority of dispatch between RES and conventional generation.

Scenarios 1–4 in Table 2 are shown for comparison, as they refer to the simulation results when wind farms are separately considered and base their bidding strategy on each farm's own forecasting model. Scenarios 5–7 simulate a VPP consisting of a group of 4, 3 or 2 wind farms, respectively. The forecasting model for scenarios 5–7 is applied on the aggregate single output curve and compared with the summation of individual farms. For example, profit in scenario 7 is compared to the summation of profits taken from scenarios 1 and 3. Profit in scenario 6 is compared to the summation of profits from scenarios 1, 2 and 3. Scenarios 8 and 9 consider the participation of the BPP with all four wind farms, for BPP scheduled at 60% and 70%, respectively. Scenarios 10–13 simulate a smaller-sized VPP consisting of a subgroup of the wind farms and the BPP, scheduled at either 60% or 70%.

Scenarios 8–13 examine different groups of wind farms, backed up by the BPP. Relatively larger sized wind farms (WF2 and WF4) were not considered in some scenarios, in order to allow a higher percentage of BPP backup power to compensate for the total wind imbalance. This allows investigating the effects of the ratio between WF power output to the dispatchable plant nominal power (which is required to cover the wind imbalance).

The cases represent different assumptions for any positive imbalance volume sales in the balancing market. The UK has a single pricing system for the imbalance settlement, hence the expected advantage of the VPP would not show up as clearly as in a dual pricing system. The assumption for the cases assumed are:

Case 1: Positive imbalance volume is sold 100% in the balancing market see also analysis in Section 4.1). This case is an analogy for the enforcement of EU Directive 2009/28/EC in which the system operators should give priority of dispatch to renewable generators over fossil fuel-based power plants [47].

Case 2: When actual imbalance in the market (derived from historical data) is positive, and the VPP has a surplus, the VPP can sell the entire positive imbalance. When actual imbalance is negative, the VPP is not able to sell its positive imbalance (see analysis in Section 4.2). This case would match a realistic market where the renewable sources compete with fossil fuel-based power plants for priority of dispatch.

Table 1
Constraints used in Eqs. (4)–(12).

Constraint equations	Explanation
(4)	States the cost function
(5)	Enforces the forecasted day-ahead prices to be higher than the operating cost of the scheduled portion of the BPP
(6) and (7)	Enforces u_t and y_t to be binary integers
(8)	Eq. (8) enforces the start-up costs to be included (activated) in the equation at time (t), if start-up costs are higher than operation costs at time (t) minus the values at the previous time step. For example: if the plant at t_1 is at rest (u_{t1}=0) and started to operate at t_2 (u_{t2}=1), the start-up cost binary should be 1 which is equal to the difference between (u_{t2}-u_{t1}). If the BPP keeps operating at t_3 then u_{t3} will be equal to u_{t2}, hence $u_{t3} - u_{t2} = 0$ and y_{t3} should be equal to 0, leading to the constraint being satisfied
(9)	Sets the output power limits for the BPP power output as a percentage of the rated power to be scheduled in day-ahead market
(10)	Sets the limits for the total BPP output power, which includes the scheduled portion and imbalances
(11)	Enforces that the BPP output power in the balancing market (P_t^{ImbBPP}) i.e. the not scheduled remainder, is equal to the difference between the actual and scheduled wind power, while keeping the total output power below the BPP nominal power, as in Eq. (11)
(12)	Sets the ramping limits for the BPP

Table 2
Scenarios breakdown by nominal power and involved generators; Ticks (✓) show if the plant is included within the VPP in the corresponding scenario.

Scenario #	WF1 Toddleburn	WF2 Minisca	WF3 Dalswinton	WF4 Edinbane	BPP (60%*) Stevens Croft	BPP (70%*) Stevens Croft
Nominal Power (MW)	27.6	36.8	30	41.4	44	44
1 (27.6 MW)	✓	–	–	–	–	–
2 (36.9 MW)	–	✓	–	–	–	–
3 (30 MW)	–	–	✓	–	–	–
4 (41.4 MW)	–	–	–	✓	–	–
5 (135.8 MW)	✓	✓	✓	✓	–	–
6 (94.4 MW)	✓	✓	✓	–	–	–
7 (57.6 MW)	✓	–	✓	–	–	–
8 (179.8 MW)	✓	✓	✓	✓	✓	
9 (179.8 MW)	✓	✓	✓	✓	–	✓
10 (138.4 MW)	✓	✓	✓	–	✓	–
11 (138.4 MW)	✓	✓	✓	–	–	✓
12 (101.6 MW)	✓	–	✓	–	✓	–
13 (101.6 MW)	✓	–	✓	–	–	✓

* 60% and 70% represent the portion of the BPP scheduled for the day-ahead market.

In real-world applications, the first case may not be considered very practical, since the simulation is unaware of the actual market status or the actions of other balancing players, who are able to purchase the surplus energy generated. However, evaluation of VPP performance in such a case, is required, as a unified forecast should give both lower positive and lower negative imbalances. The unified forecast might be less profitable when compared to individual operation of wind farms. For individual operation, the difference between actual generated and forecasted power might result in larger positive imbalance in total. This would also result in compensation for the penalties coming from negative imbalances. Eventually the VPP becomes less profitable because it produces lower positive imbalance, as well as lower negative imbalance.

The second case is considered to be more realistic, since the positive imbalance is sold when the market experiences an energy deficit. The VPP is restricted from selling any surplus when the market is already experiencing a positive imbalance. In this case, purchasing additional energy from the system operator would lead to unaccepted system stability. Simulation results for all considered cases and scenarios are shown in the following section.

4. Results & discussion

For each scenario considered, the summation of profits of individual plants is presented and compared against the single forecasting of the VPP (see Tables 3 and 4 for Case 1 and Tables 5 and 6 for Case 2). Bidding is assumed to take place at 12:00, as in the real market, hence, there is no wind energy scheduled for the starting period between 0:00 to 12:00.Simulation results are calculated for the steps 25–4248 (i.e. for a total of 88 days per season and a time step of 30 min).

The profitability of the VPP is determined by the criterion of the average selling price, defined as the total profit divided by the total actual output. In addition, the remaining negative imbalance summation is reported and compared against the summation value for individual plant operation. The latter determines the evaluation of the VPP effects on negative imbalances.

Forecasting is achieved by the ARMA forecasting technique. The ARMA(p,q) model order was obtained for each wind farm separately and for the VPP by aggregating the actual generation of wind farms for the period of December 2016 (training data). Models orders were obtained by trial and error and different parameter combinations for p = [1, 9] and q = [1, 9] and based on the minimum AIC value. For WFs, the ARMA models were assumed to be seasonal with 4 periods and seasonal differencing, which considered a seasonal weekly pattern of the wind for the one-month duration training data. The VPP ARMA model assumed 2 seasonal differences, which proved to give better results by trial and error.

WF1:	$ARMA(7, 8)_4$ with AIC = 9681
WF2:	$ARMA(8, 9)_4$ with AIC = 9798
WF3:	$ARMA(9, 9)_4$ with AIC = 8414
WF4:	$ARMA(8, 5)_4$ with AIC = 10046
Day-ahead price:	$ARMA(8, 8)_4$ with AIC = 1578
VPP Single forecast:	$ARMA(6, 7)_2$ with AIC = 11264

Fig. 3 shows the forecasted prices, the day-ahead prices and imbalance prices, for 30 days in winter and summer, respectively, with a time step of 30 min and for 48 settlement periods. Results for a typical day are shown in Fig. 4.

Day-ahead prices fluctuate around 53 GBP/MWh in winter, as shown in Fig. 3-(1) and 41 GPB/MWh in the summer (see also Fig. 3-(2)) with a maximum of 146.2 GBP/MWh and 115 GBP/MWh, and a minimum of 28.8 GBP/MWh and 14.9 GBP/MWh, respectively. As shown in Fig. 3-(3), the imbalance prices fluctuate around 54 GBP/MWh in winter (for both up regulation and down regulation) with a maximum of 146 GBP/MWh and a minimum of 28.8 GBP/MWh. Summer imbalance prices (see Fig. 3-(4)) mean value is 37.5 GBP/MWh with a maximum of 292.5 GBP/MWh and a minimum of 0. The difference between the day-ahead and imbalance prices is small, resulting in a small difference also between the sales of the positive imbalance volume in the balancing market and the generated energy in the day-ahead market. More detailed results are presented in Tables 3 and 4 for Case 1 and Tables 5 and 6 for Case 2.

Figs. 4 and 5 show the forecasted wind power in comparison to actual wind power output in winter and summer. Forecasting method accuracy for day-ahead prices is measured by the Root Mean Square Error (RMSE) for the period under examination (3 months in winter and 3 months in summer).

The RMSE values for each individual wind farm forecasted power in winter were estimated at 9.38, 10.39, 6.77, and 10.20 for WF1, WF2, WF3 and WF4, respectively. The RMSE values for summer (see also Fig. 6) were estimated at 6.76, 7.17, 4.65, and 7.99 for WF1, WF2, WF3 and WF4, respectively. Observed performance in the accuracy of the forecasting technique can be attributed to the long-term forecast horizon (12–36 h), as the plant operators need to submit their bids every day at noon.

Table 3
Case 1, Winter results summary. Refer to Appendix A for the bullets (*) and captions explanations.

Scenario #	Cumulative Profit (millions GBP)	Selling Price (GBP/MWh)*	Profit Increase % **	Remaining Negative Imbalance (GWh)	Total Actual Energy Produced (GWh)	Negative Imbalance /Energy Produced %
1	1.87	46.98		-12.9	39.8	32.5
2	2.16	44.83		-16.7	48.3	35
3	1.45	44.46		-10.2	32.7	31
4	3.07	48.41		-13.2	63.4	21
ΣWF 1- 4	8.56	46.46**		-53	184.4	29
5	8.6	46.67	0.45	-40.3	184.4	22
ΣWF 1- 3	5.49	45.44**		-39.8	120.9	33
6	5.5	45.54	0.22	-28.8	120.9	24
WF1 +WF3	3.32	45.84**		-23.1	72.6	32
7	3.31	45.62	-0.49	-18.8	72.6	26
8	15.1	46.78	0.68	-17.5	321.4	5.46
9	15.6	46.83	0.86	-20.3	332.9	6.10
10	11.7	46.20	1.60	-10.1	253.3	3.97
11	12.3	46.33	1.90	-11.8	266	4.45
12	9.25	46.36	1.13	-4.6	199.7	2.31
13	9.94	46.51	1.40	-5.4	213.7	2.51

Forecasting accuracy, however, was not the major focus of this study. The level of accuracy is similar in all scenarios and this allows for a reasonable comparison and evaluation of the profitability of the VPP. Prices forecasting (which have a relatively predictable and almost repeating pattern) appear to perform better than wind power forecasting, which signifies that seasonal ARMA parameters may have to be revisited in future work and may not be the most suitable method for the consideration of observed high spikes. Further investigation is required to mitigate potentially erroneous forecasts that resemble similar behaviour. Results from the simulations are presented in the following section.

4.1. Case 1

In case 1, the positive imbalance is entirely sold in the balancing market.

The "Profit increase" column shown in Tables 3 and 4 is the anchor point on which conclusions from this work are based; the values in this

Table 4
Case 1, Summer results summary. Refer to Appendix A for the bullets (*) and captions explanations.

Scenario #	Cumulative Profit (millions GBP)	Selling Price (GBP/MWh)*	Profit Increase % **	Remaining Negative Imbalance (GWh)	Total Actual Energy Produced (GWh)	Negative Imbalance /Energy Produced %
1	0.97	40.02		-10.8	24.3	44.5
2	1.22	40.82		-13.4	29.9	45
3	0.78	41.31		-7.7	19.1	40
4	1.62	42.50		-11.2	38.3	29
ΣWF 1- 4	4.61	41.31**		-43.1	111.6	39
5	4.63	41.50	0.48	-30.3	111.6	27
ΣWF 1- 3	2.98	40.68**		-31.9	73.4	43
6	3	40.89	0.51	-23.4	73.4	33
WF1 +WF3	1.76	40.58**		-18.5	43.4	43
7	1.77	41.00	1.03	-14.4	43.4	33
8	10.11	41.44	0.33	-9.2	244	3.78
9	10.61	41.57	0.64	-10.5	255.3	4.11
10	8.31	41.23	1.34	-6.2	201.6	3.08
11	8.84	41.41	1.79	-6.9	213,5	3.25
12	6.82	41.43	2.09	-3.1	164,7	1.91
13	7.38	41.64	2.61	-3.3	177.3	1.88

Table 5
Case 2 Winter results summary. Refer to Appendix A for the bullets (*) and captions explanations.

Scenario #	Cumulative Profit (millions GBP)	Selling Price (GBP/MWh)*	Profit Increase % **	Remaining Negative Imbalance (GWh)	Total Actual Energy Produced (GWh)	Negative Imbalance /Energy Produced %
1	1.6	40.24		-12.9	39.8	32
2	1.93	39.97		-16.7	48.3	35
3	1.31	39.87		-10.2	32.8	31
4	2.76	43.54		-13.2	63.5	21
ΣWF 1- 4	7.6	41.24		-53	184.4	29
5	7.9	42.92	4.07	-40.3	184.4	22
ΣWF 1- 3	4.84	40.03		-39.8	121	33
6	4.97	41.14	2.77	-28.8	121	24
WF1 +WF3	2.91	40.07		-23.1	72.6	32
7	3	41.26	2.98	-18.8	72.6	26
8	14.2	44.35	7.55	-18	320.1	5.6
9	14.67	44.38	7.61	-21.6	330.7	6.5
10	11.05	43.76	9.31	-10.3	252.6	4.1
11	11.6	43.85	9.55	-12.7	264.4	4.8
12	8.85	44.35	10.68	-4.7	199.5	2.3
13	9.46	44.41	10.82	-5.8	21	2.7

column provide the basis for comparison between the VPP scenario and the operation with individual wind farms. For scenarios 8–13 with BPP, profits are compared to wind farms only. For example, in scenarios 8 and 9 (aggregation of all wind farms and BPP) profit is compared to summation of individual wind farms (WF1 + WF2 + WF3 + WF4). For scenarios 10 and 11, profits are compared to a subgroup of wind farms (WF1 + WF2 + WF3).

A negative profit for winter is observed in scenario 7, which might be due to higher sales for WF1 and WF3 in the balancing market coinciding with periods of high prices. WF1 and WF3 produce higher

Table 6
Case 2 Summer results summary. Refer to Appendix A for the bullets (*) and captions explanations.

Scenario #	Cumulative Profit (millions GBP)	Selling Price (GBP/MWh)*	Profit Increase % **	Remaining Negative Imbalance (GWh)	Total Actual Energy Produced (GWh)	Negative Imbalance /Energy Produced %
1	0.83	34.19		-10.8	24.3	44.5
2	1.07	35.68		-13.4	30	45
3	0.68	35.57		-7.7	19.1	40
4	1.41	36.79		-11.2	38.3	29
ΣWF 1- 4	3.99	35.72		-43.1	111.6	39
5	4.19	37.59	5.24	-30.3	111.6	27
ΣWF 1- 3	2.58	35.16		-31.9	73.4	43.5
6	2.68	36.51	3.84	-23.4	73.4	32
WF1 +WF3	1.51	34.80		-18.5	43.4	43
7	1.58	36.43	4.69	-14.4	43.4	33
8	9.44	38.92	8.97	-13	242.5	5.3
9	9.8	38.88	8.85	-15.2	252.1	6.0
10	7.78	38.77	10.29	-9.3	200.6	4.6
11	8.19	38.74	10.19	-10.6	211.4	5.0
12	6.46	39.25	12.81	-5.1	164.5	3.1
13	6.91	39.13	12.44	-5.5	176.7	3.11

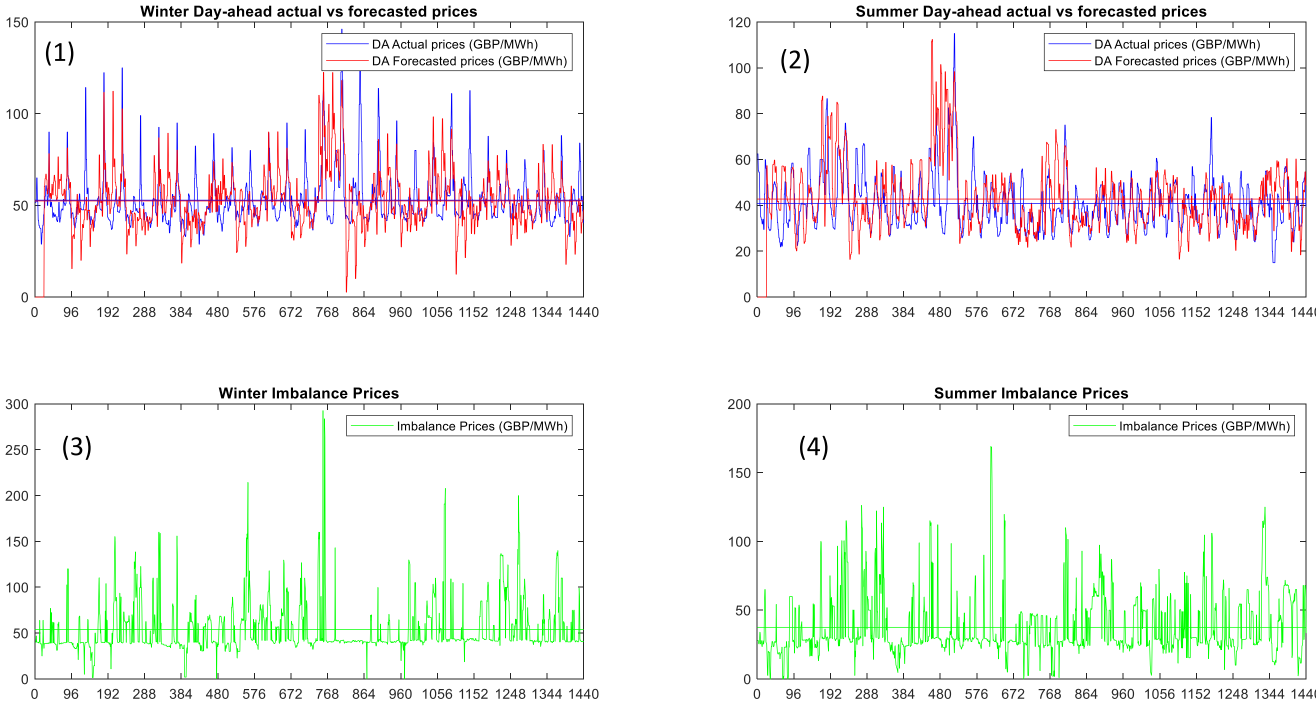

Fig. 3. Actual day-ahead, forecasted day-ahead and imbalance prices in winter (1, 3) and summer (2, 4). Straight lines in the figures represent mean values for the full duration of the simulation analysis. The time step is 0.5 h (30 min), resulting in 48 settlement periods per day and 1440 points per month.

positive imbalance in this case. On the other hand, all VPP Models yield both lower negative and lower positive imbalance. These results show greater suitability in a dual pricing market, where the contrast in profits for VPP and individual plant operation would be clearer. An example of operation across 48 h that highlights this result is shown in Fig. 7.

The highest profit increase in winter in the scenarios without integrating the BPP is scenario 5 where the 4 plants output power is forecasted as a single output. In summer, the highest profit increase is

Fig. 4. Actual vs forecasted day-ahead prices for day 9.

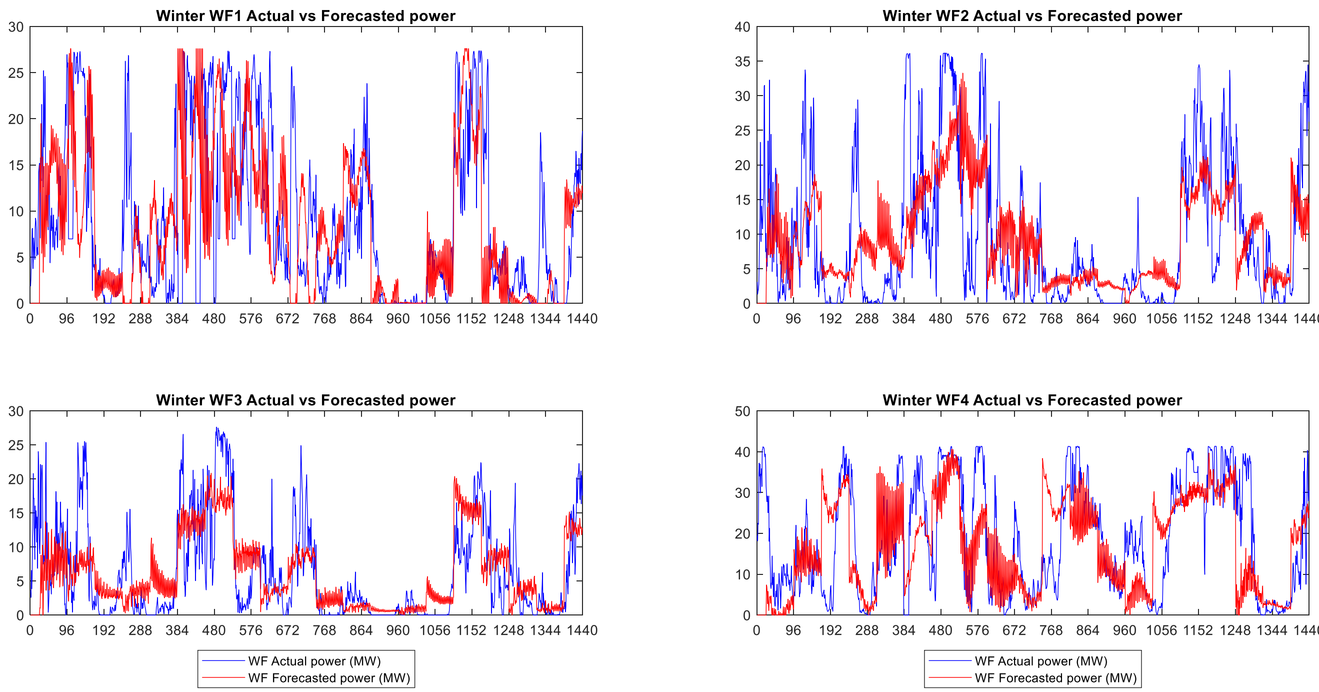

Fig. 5. Winter individual wind farms actual generated power.

for the 2 wind farms operating together as shown in Table 4. Integration of the BPP to the VPP model (scenarios 8–13) achieves a significant decrease in the negative imbalance, which ranges between 1.9% and 6.0% in winter and summer, respectively. Higher profits are achieved in the 70–30% models (i.e. scenarios 9, 11 and 13), where the BPP is able to better compensate for wind imbalances by 30% of its nominal power.

In winter, higher profits were achieved in scenario 11 with a profit increase of 1.90%.The corresponding VPP in summer achieved 1.79%, resulting in a profit increase if 1.85%, on average. Similarly, the most profitable VPP model in summer is VPP was obtained in scenario 13 with a 2.61% profit increase. In winter, the corresponding model achieved 1.40% profit increase, leading to an average profit increase of 2.00%. In addition, scenarios 12 and 13 obtained the lowest negative imbalance among all scenarios, therefore it can be concluded that for

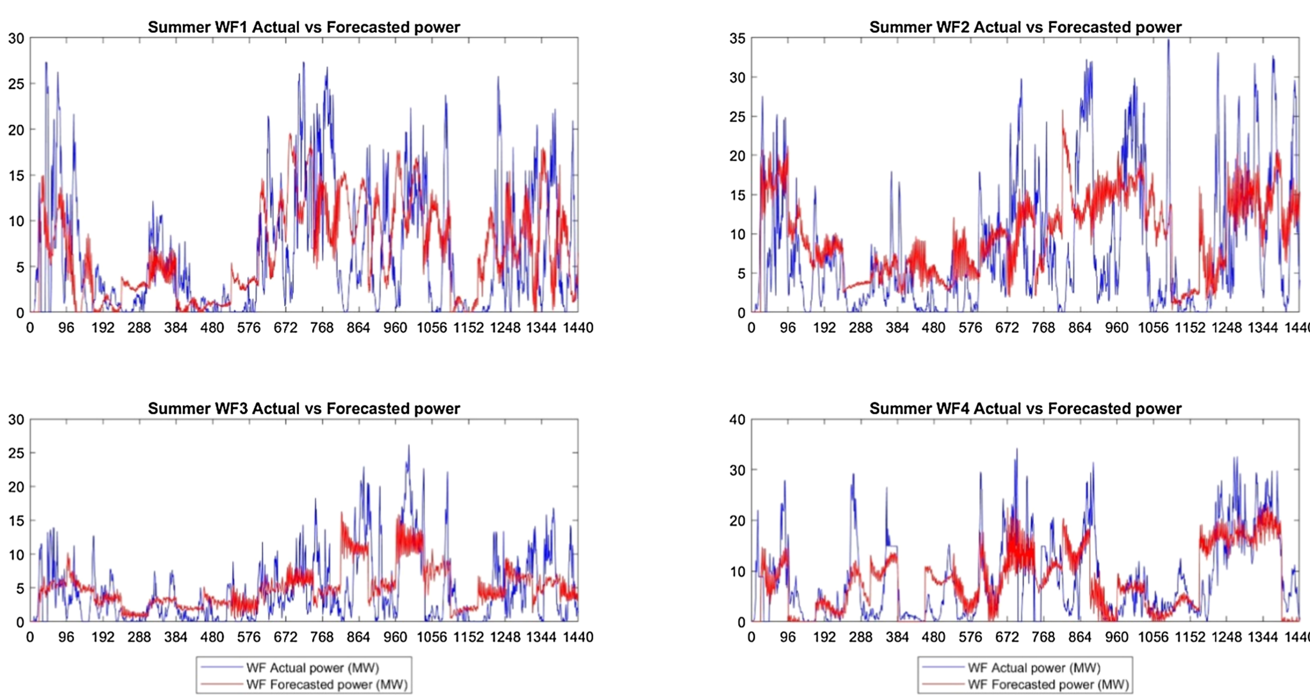

Fig. 6. Summer individual wind farms actual generated power.

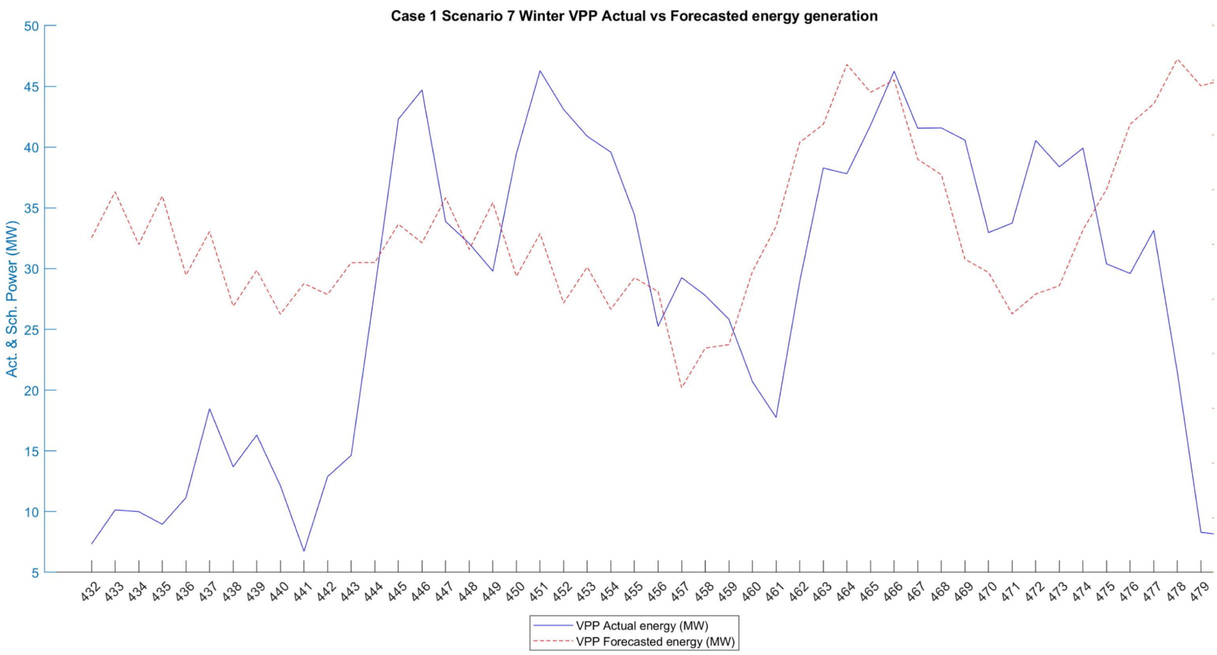

Fig. 7. Case 1 Scenario 7 with a negative profitability.

VPP operation, scenario 13 obtained the optimal results for Case 1.

While the 70–30% model presented higher profits, a slightly higher negative imbalance was also observed. In addition, the BPP responds well to imbalances with two wind farms (scenarios 12 and 13) with imbalance percentages of 2.30% and 2.50% in winter and 1.90%, 1.90% in summer, and moderately good with three wind farms (scenarios 10 and 11). The BPP response seems to perform better with two wind farms as the imbalance volume (in MWh) from these farms of

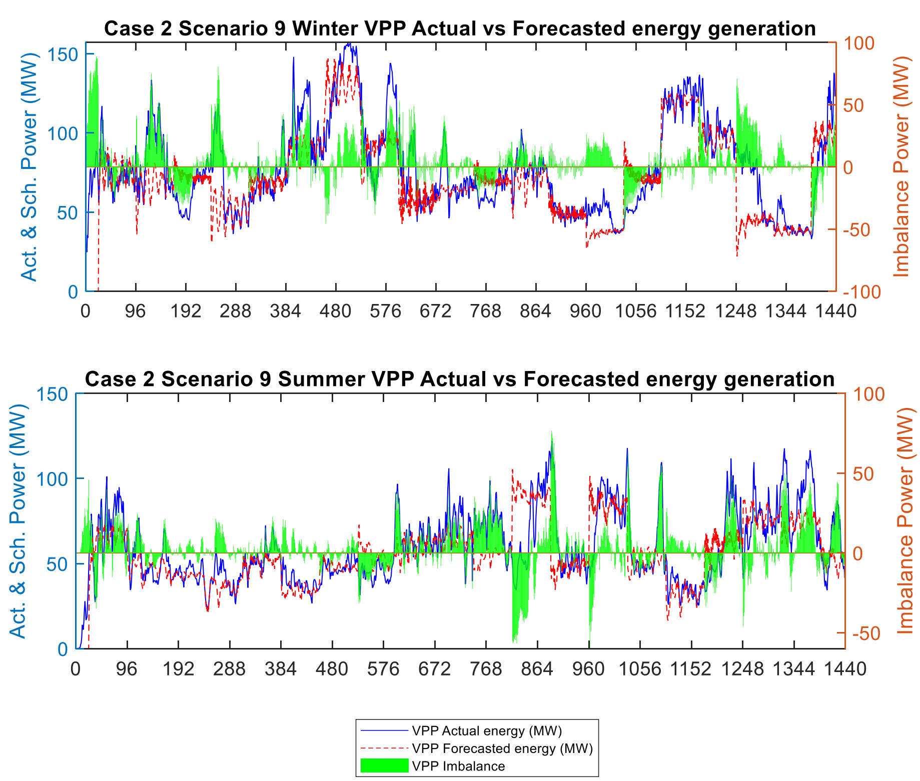

Fig. 8. Case 2 VPP (Wind Farms + Biomass plant with 30% assigned for imbalance compensation) – Scenario 9 gives the least profitable model of the Wind + Biomass combination (Average annual profit increase = 8%).

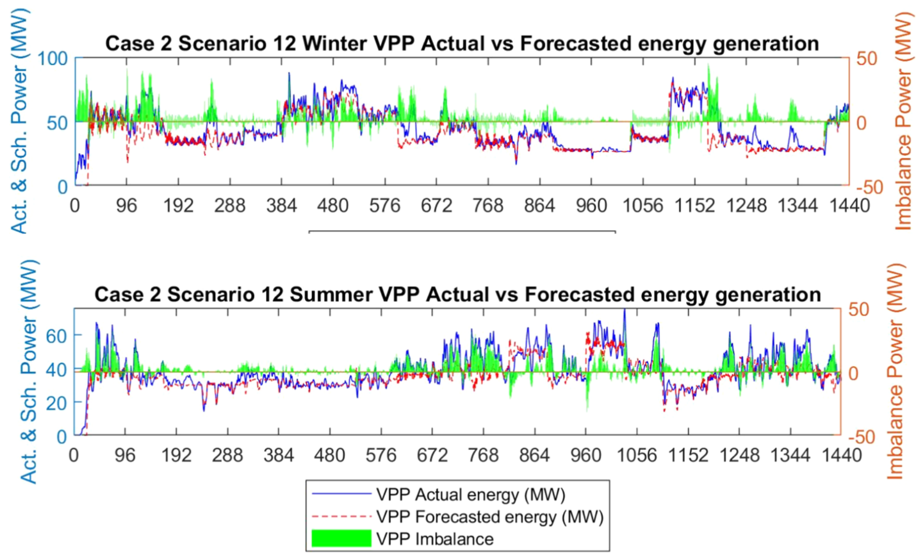

Fig. 9. Case 2 VPP (Wind Farms + Biomass plant with 40% assigned for imbalance compensation) – Scenario 12 is giving the most profitable model of the Wind + Biomass combination (Average annual profit increase = 12%).

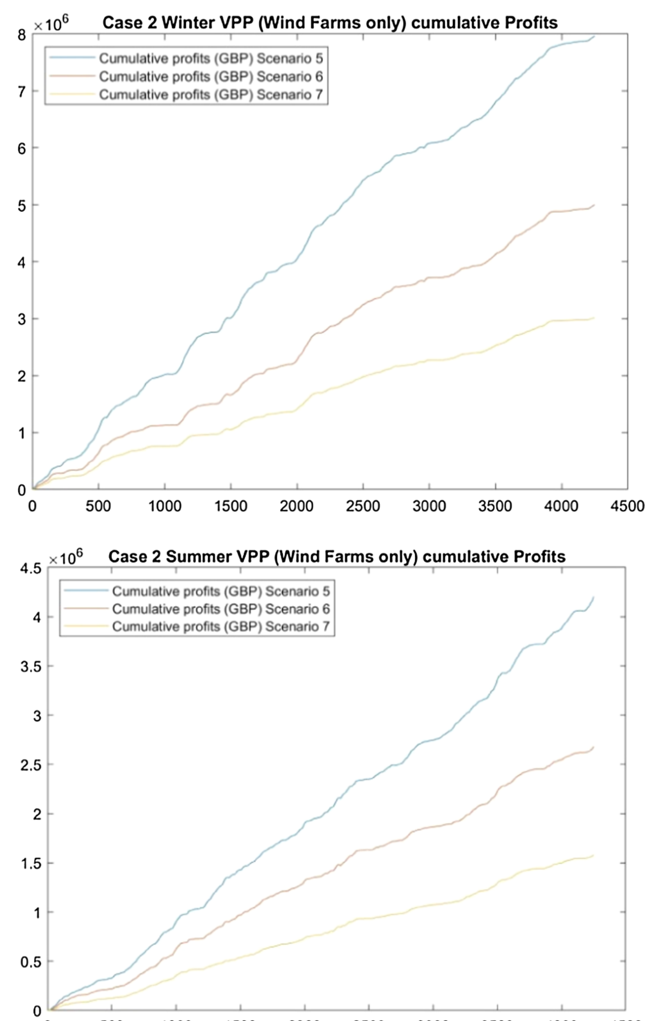

Fig. 10. Case 2 VPP Wind Farms only, cumulative profits over the full study period.

nominal sizes 27.6 and 30 MW), respectively, was almost equivalent to the remaining portion of the BPP, allowed to participate in the balancing market.

4.2. Case 2

In this case, positive imbalance is sold only when the VPP has a surplus power and the market experiences a shortage in supply.

The profitability of the VPP for all scenarios is clearly shown in Tables 5 and 6. The highest increase in profits for the VPP (Wind farms combined) as compared to the sum of the individual wind farms is 4.07% in winter and 5.24% in summer (scenario 5). The smallest profit increase occurs in scenario 6 with 3.84% in summer and 2.77% in winter. In this scenario, 'Edinbane', the wind farm with the largest nominal power is removed from the model. For the biomass scenarios (8 to 13), a significant reduction in the negative imbalance was observed. Negative imbalance reduced to 2.30% in winter (scenario 12) and to 3.11% in summer (scenario 13). A maximum profit increase of 10.68% was observed in winter for scenario 13, and 12.81% in summer for scenario 12.

The best performing scenario for Case 2 was the VPP in scenario 12 (2 Wind Farms and 40% dedicated BPP for imbalance), with an observed profit increase of 12%, a significant increase for a prospective investor.

Similarly to case 1, VPP operation with a backup plant responds better to committed schedule, resulting in better overall performance, as shown in Figs. 8–10. In Case 1 both negative and positive imbalance volumes are lower than those obtained from each individual wind farm, but in case 2 the positive imbalance is not entirely sold, leading to some wind surplus being curtailed.

Case 2 results place emphasis on the lower positive imbalance. The benefits of the VPP are shown here by the comparison of the VPP operation against individual farms operation with regards to the negative imbalance, which makes the VPP a more profitable case.

A similar study on a large scale VPP consisting of 600 MW wind farms and battery storage system yielded a profit increase of 1.3% and 3.2% for two different strategies, as stated in [48]. The result of this

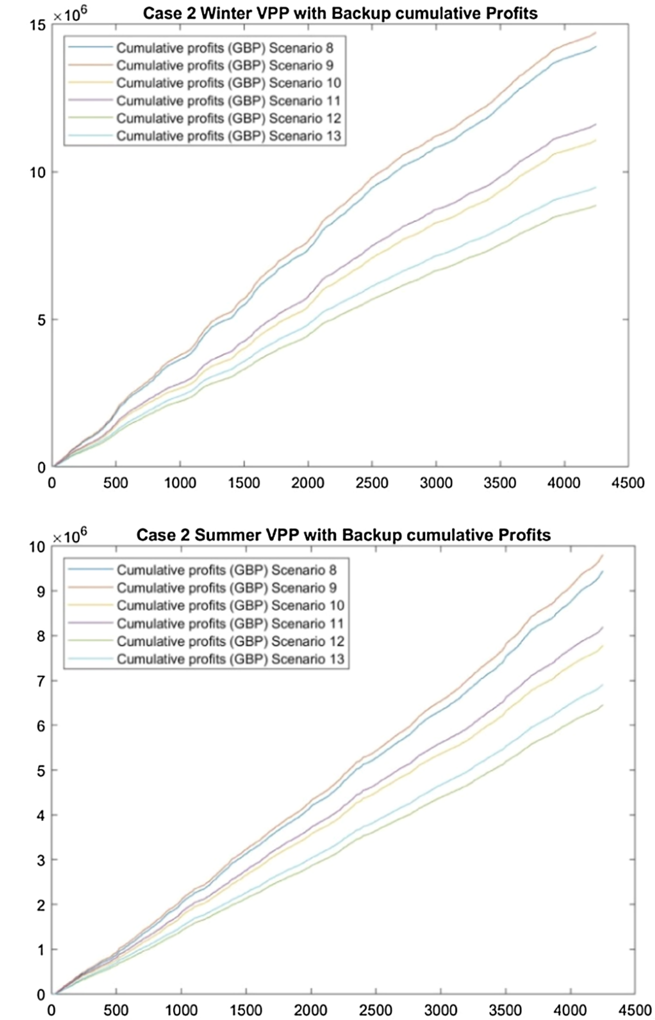

Fig. 11. Case 2 VPP with backup power, cumulative profits over the full study period for the six different scenarios.

study are comparable to results found in this work, especially with results from scenarios 5 to 7 (Table 2). Addition of the biomass dispatchable plant improved profits by up to 12% (Table 6).

The main objective for the aggregation of different power plants is to reduce uncertainties and minimize deviations from energy schedule. In this study, this is achieved, however, in Case 1, this also resulted in lower positive imbalance, which subsequently also reduced the value added by the VPP. In this case, revenue surplus sales from individual farms exceeded the penalties imposed on these farms due to negative imbalance. Cumulative profits curves for VPP with backup power models, as shown in Fig. 11, are smoother and tend to present a similar linear behaviour, as results for VPP with wind farms only, shown in Fig. 10.

5. Conclusion

This study highlights the importance of aggregating different renewable technologies rather than combining multiple DERs of the same technology type in VPPs. More important, this study shows the added value brought by the inclusion of a controllable plant or storage system working in partnership with intermittent energy generation sources. The concept of CVPPs proved to yield higher profits and reduced uncertainty, even in the case of a less powerful forecasting model. Accurate forecasting, especially for wholesale energy prices, is a crucial factor to efficiently schedule thermal plant operation, decided based on the relation of variable operating costs to the market prices. Moreover, as shown in this study, significant errors in the day-ahead prices forecasting may result in a lower scheduled BPP power, essentially leading to reduced potential sales.

Any backup plants to be considered for collaboration with intermittent sources, should be of suitable size to compensate for the forecasting error in an effective way. Results from both different cases considered in this study, indicate that a ratio of backup power to wind power of 20–30% is most favourable and may yield higher profits. This ratio might change relatively to the wind farm location and potentially the forecasting technique used.

The forecasting error of the technique used in this study was high. Moreover, day-ahead forecasts always face greater uncertainty risks due to the longer forecast time horizon. Forecasting errors typically range between 5% and 10%, as estimated from sample studies found in the literature for Europe and the USA [49] (e.g. in Sweden, the majority of forecasted samples yielded a 10% error, a similar case was observed in Germany but with lower deviation from the mean). Better performance in forecasting would lower the ramping of the backup plant, while also reducing the required ratio between the rated power of the thermal plant to capacities from wind farms. Better forecasts would also allow a higher percentage of the thermal plant to be scheduled as a base load, making the operation of the BPP more efficient and more profitable.

Annual variation of wind speed (assuming 20% average annual increase/decrease in wind speed), resulted in almost constant profit increase of VPP scenarios compared to individual wind farms operation. This result is expected, since wind patterns did not change and forecasting errors are similar, although overall revenue observed was higher/lower as wind farms produce more/less power, respectively.

The results highlight the need for future research in the following directions:

- Examination of a similar VPP model in a dual imbalance pricing system would prove very valuable. This could potentially result in lower profits coming from positive imbalance sales and higher costs for energy purchase that covers negative imbalance. Hence, the VPP profits could be higher in this case.
- Improvement of the forecasting model and of the performance of the forecasting algorithm could potentially be achieved by the use of ANN models and multiple input variables, such as wind speed, air temperature and consideration of wind turbines orientation.
- The VPP could benefit by the inclusion of a storage system; the positive imbalance would be stored and re-used to compensate for energy shortages. This would reduce the need for another backup plant if the total wind output is significantly higher than the dispatchable plant. Future work would focus a similar VPP model with pumped hydro storage or battery. The optimization in this case would also need to derive the suitable storage system size and dispatchable plant operation.
- Simulating a VPP model with an integrated solar plant is considered for future work. The aggregation of biomass and wind generation studied in this work brought significant benefits. Addition of different RES technologies with diverse output characteristics, such as solar generation, could potentially yield further improvements in the profits achieved.

Appendix A

Case 1

See Tables 7 and 8.

Table 7
Detailed results for Case 1, winter.

Scenario #	Cumulative Profit (millions GBP)	Selling Price (GBP/MWh)*	Profit Increase % **	Remaining Negative Imbalance (MWh)	Scheduled Energy (MWh)	Actual Energy Sold (MWh)	Positive Imbalance (MWh)	Total Actual Energy Produced (MWh)	Negative Imbalance /Energy Produced %
1	1,870,702	46.98		-12,913	36,541	39,815	16,186	39,815	32.5
2	2,166,328	44.83		-16,715	48,057	48,323	16,982	48,323	35
3	1,457,424	44.46		-10,198	31,897	32,784	11,085	32,784	31
4	3,071,862	48.41		-13,165	58,366	63,454	18,253	63,454	21
ΣWF 1- 4	**8,566,316**	**46.46**		**-52,992**	**174,862**	**184,376**	**62,506**	**184,376**	**29**
5	8,604,741	46.67	0.45	-40,282	178,800	184,376	45,858	184,376	22
ΣWF 1- 3	**5,494,455**	**45.44**		**-39,827**	**116,495**	**120,922**	**44,253**	**120,922**	**33**
6	5,506,722	45.54	0.22	-28,802	113,328	120,922	36,396	120,922	24
WF1 +WF3	**3,328,127**	**45.84**		**-23,111**	**68,438**	**72,599**	**27,272**	**72,599**	**32**
7	3,311,715	45.62	-0.49	-18,845	68,791	72,599	22,653	72,599	26
8	15,035,206	46.78	0.68	-17,547	288,347	321,395	50,594	321,395	5.46
9	15,591,194	46.83	0.86	-20,306	303,312	332,943	49,937	332,943	6.10
10	11,702,305	46.20	1.6	-10,061	222,874	253,281	40,467	253,281	3.97
11	12,325,220	46.33	1.9	-11,834	237,839	266,038	40,033	266,038	4.45
12	9,255,977	46.36	1.13	-4,608	178,338	199,661	25,931	199,661	2.31
13	9,939,054	46.51	1.4	-5,364	193,302	213,676	25,739	213,676	2.51

Table 8
Detailed results for Case 1, summer.

Scenario #	Cumulative Profit (millions GBP)	Selling Price (GBP/MWh)*	Profit Increase % **	Remaining Negative Imbalance (MWh)	Scheduled Energy (MWh)	Actual Energy Sold (MWh)	Positive Imbalance (MWh)	Total Actual Energy Produced (MWh)	Negative Imbalance /Energy Produced %
1	973,049	40.02		-10,814	25,101	24,317	10,030	24,317	44.5
2	1,224,037	40.82		-13,426	33,402	29,984	10,008	29,984	45
3	787,884	41.31		-7,659	19,788	19,074	6,945	19,074	40
4	1,626,475	42.50		-11,159	36,982	38,267	12,443	38,267	29
ΣWF 1- 4	4,611,445	41.31		-43,057	115,273	111,641	39,426	111,641	39
5	4,633,580	41.50	0.48	-30,274	113,349	111,641	28,566	111,641	27
ΣWF 1- 3	2,984,970	40.68		-31,898	78,290	73,374	26,983	73,374	43
6	3,000,068	40.89	0.51	-23,434	74,957	73,374	21,851	73,374	33
WF1 +WF3	1,760,933	40.58		-18,473	44,889	43,391	16,975	43,391	43
7	1,779,030	41.00	1.03	-14,374	44,285	43,391	13,480	43,391	33
8	10,111,743	41.44	0.33	-9,227	220,863	244,002	32,366	244,002	3.78
9	10,610,822	41.57	0.64	-10,494	233,787	255,260	31,966	255,260	4.11
10	8,309,478	41.23	1.34	-6,209	182,471	201,554	25,293	201,554	3.08
11	8,839,105	41.41	1.79	-6,936	195,395	213,452	24,992	213,452	3.25
12	6,823,173	41.43	2.09	-3,138	151,799	164,683	16,022	164,683	1.91
13	7,383,989	41.64	2.61	-3,335	164,724	177,323	15,934	177,323	1.88

Least profitability among the Wind-Only aggregated VPP.
Best profitability among the Wind-Only aggregated VPP.
Least profitability among the Wind-BPP aggregated VPP.
Best profitability among the Wind-BPP aggregated VPP.

* Average selling price is an index to benchmark and compare the aggregated plants profitability; it is equal to the cumulative profit divided by the total actual energy produced.

** The profit increase is measured by comparing the selling price of the VPP to the corresponding selling price of the summation of individual farms (Ex: In Summer table, the profit increase of VPP-Scenario 7 = (Selling price of Scenario 7 (41 GBP)/Selling price of WF1 + WF3 (40.58)) % = 101.03%, hence, the increase is 1.03%.

Case 2 – Results Tables

See Table 9 and 10.

Table 9
Detailed results for Case 2, winter.

Scenario #	Cumulative Profit (millions GBP)	Selling Price (GBP/MWh)*	Profit Increase % **	Remaining Negative Imbalance (MWh)	Scheduled Energy (MWh)	Actual Energy Sold (MWh)	Positive Imbalance (MWh)	Total Actual Energy Produced (MWh)	Negative Imbalance /Energy Produced %
1	1,602,025	40.24		-12,913	36,541	35,627	11,999	39,815	32
2	1,931,352	39.97		-16,715	48,057	44,530	13,188	48,323	35
3	1,307,053	39.87		-10,198	31,897	30,355	8,657	32,784	31
4	2,762,785	43.54		-13,165	58,366	58,914	13,712	63,454	21
ΣWF 1- 4	7,603,215	41.24		-52,992	174,862	169,426	47,556	184,376	29
5	7,912,502	42.92	4.07	-40,282	178,800	173,474	34,955	184,376	22
ΣWF 1- 3	4,840,430	40.03		-39,827	116,495	110,512	33,844	120,922	33
6	4,974,662	41.14	2.77	-28,802	113,328	112,401	27,875	120,922	24
WF1 +WF3	2,909,079	40.07		-23,111	68,438	65,982	20,655	72,599	32
7	2,995,711	41.26	2.98	-18,845	68,791	67,545	17,599	72,599	26
8	14,197,712	44.35	7.55	-18,020	288,347	308,221	37,894	320,111	5.6
9	14,674,160	44.38	7.61	-21,596	303,312	319,007	37,291	330,667	6.5
10	11,053,663	43.76	9.31	-10,322	222,874	243,145	30,593	252,621	4.1
11	11,595,787	43.85	9.55	-12,768	237,839	255,152	30,081	264,429	4.8
12	8,846,999	44.35	10.68	-4,682	178,338	193,571	19,916	199,474	2.3
13	9,456,289	44.41	10.82	-5,794	193,302	207,128	19,620	212,955	2.7

Table 10
Detailed results for Case 2, winter.

Scenario #	Cumulative Profit (millions GBP)	Selling Price (GBP/MWh)*	Profit Increase % **	Remaining Negative Imbalance (MWh)	Scheduled Energy (MWh)	Actual Energy Sold (MWh)	Positive Imbalance (MWh)	Total Actual Energy Produced (MWh)	Negative Imbalance /Energy Produced %
1	831,436	34.19		-10,814	25,101	21,558	7,270	24,317	44.5
2	1,069,767	35.68		-13,426	33,402	26,971	6,995	29,984	45
3	678,368	35.57		-7,659	19,788	16,995	4,866	19,074	40
4	1,407,750	36.79		-11,159	36,982	34,209	8,385	38,267	29
ΣWF 1- 4	3,987,321	35.72		-43,057	115,273	99,732	27,517	111,641	39
5	4,196,187	37.59	5.24	-30,274	113,349	103,312	20,237	111,641	27
ΣWF 1- 3	2,579,571	35.16		-31,898	78,290	65,523	19,132	73,374	43.5
6	2,678,693	36.51	3.84	-23,434	74,957	67,192	15,668	73,374	32
WF1 +WF3	1,509,804	34.80		-18,473	44,889	38,552	12,137	43,391	43
7	1,580,606	36.43	4.69	-14,374	44,285	39,536	9,625	43,391	33
8	9,439,673	38.92	8.97	-12,958	220,863	232,653	24,748	242,536	5.5
9	9,801,403	38.88	8.85	-15,217	233,787	242,463	23,893	252,107	6.0
10	7,779,995	38.77	10.29	-9,315	182,471	192,987	19,831	200,648	4.5
11	8,189,443	38.74	10.19	-10,596	195,395	203,987	19,187	211,402	5.0
12	6,457,013	39.25	12.81	-5,103	151,799	159,344	12,648	164,505	3
13	6,912,852	39.13	12.44	-5,500	164,724	171,642	12,419	176,684	3

Least profitability among the Wind-Only aggregated VPP.
Best profitability among the Wind-Only aggregated VPP.
Least profitability among the Wind-BPP aggregated VPP.
Best profitability among the Wind-BPP aggregated VPP.
* Average selling price is an index to benchmark and compare the aggregated plants profitability; it is equal to the cumulative profit divided by the total actual energy produced.
** The profit increase is measured by comparing the selling price of the VPP to the corresponding selling price of the summation of individual farms (Ex: In Summer table, the profit increase of VPP-Scenario 7 = (Selling price of Scenario 7 (36.43 GBP)/Selling price of WF1 + WF3 (34.8)) % = 104.69%, hence, the increase is 4.69%.

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