CHARACTERISATION OF PORTFOLIOS OF DISTRIBUTED ENERGY RESOURCES UNDER UNCERTAINTY

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ABSTRACT

The paper proposes a model to determine the optimal strategy of offering electricity at the day-ahead market for a portfolio of Distributed Energy Resources. The stochastic nature of the problem is taken into account through uncertainty of generator output and forecasts of day-ahead and imbalance prices. The model attempts to maximise the expected profit of the portfolio when exposed to imbalance prices and output uncertainty. Portfolios analysed included conventional generators, wind generators, or both. The results indicate that the proposed approach is able to adapt the offering strategy to the risk profile in different times of the day. Also, significant synergic effects are demonstrated when wind and conventional generators are aggregated into a single portfolio, due to increased flexibility in internal portfolio balancing.

INTRODUCTION

Distributed Energy Resources (DERs), consisting of small-scale distributed generation and responsive loads located within distribution networks, have increasingly attracted attention in recent time [1]. This interest has been driven primarily by calls to generate more electricity from renewables, as well as to improve energy efficiency.

However, the current policy on DERs has focused on connecting rather than integrating them. This is known as the “fit and forget” approach, and comes as a legacy of a passive distribution network with unidirectional power flows. Thus far, DERs have been used to substitute electricity that would have otherwise been produced by conventional plants, but not to replace their capacity as they are not directly visible to system operators. In the future, this might create excess capacity and deteriorate asset utilisation and the overall system efficiency, in turn increasing the electricity cost paid by the end user [2].

A possible alternative to passive approach is proposed in the form of aggregating DER into controllable Virtual Power Plants (VPPs) [3]. The aggregated portfolios of DERs could then be visible to and controlled by the system and market operators, and have impact similar to a transmission connected generator. This paper focuses on the market aspect of this integration, meaning that individual DERs can gain access to all energy markets, and benefit from VPP market intelligence to maximise their revenue opportunities. The potential of the VPP concept is additionally enhanced by recent developments of Smart Grid solutions focused on providing the communication and control infrastructure for DER [4].

Commercial aggregation of DERs with pronounced output uncertainty is not a trivial task. The uncertainty stems from various sources, such as more frequent outages, variability of primary resource (as for e.g. wind), or an operating pattern dictated by non-electricity output requirements (e.g. CHP).

Characterisation of a DER portfolio in terms of market access, from the point of view of the portfolio operator, needs to provide a market strategy that will determine what quantity of electricity will be offered at the market for a given price level. The analysis in this paper will primarily focus on the day-ahead market and subsequent settlement of imbalances at the balancing market. However, similar reasoning can be used even if multiple market segments (e.g. longer-term bilateral forward markets) are addressed simultaneously.

CHARACTERISATION METHODOLOGY

The characterisation of a DER portfolio is carried out using the techniques of stochastic programming with the aim of determining optimal quantities of electricity that are to be offered in the day-ahead market for a given set (or probability distributions) of day-ahead and imbalance prices.

Stochastic Programming

Stochastic programming is a framework for modelling optimisation problems that involve uncertainty [5]. Its goal is to find a policy that maximises or minimises the expectation of some function of the decisions and the random variables.

The most widely applied and studied stochastic programming models are *two-stage linear programs*. Here the decision maker takes some action in the first stage, after which a random event (or a series of events) occurs, affecting the outcome of the first-stage decision. A recourse decision can then be made in the second stage to rectify the effects experienced as a result of the first-stage decision. The optimal policy from such a model is a single first-stage policy and a collection of recourse decisions (a decision rule) defining which second-stage action should be taken in response to each random outcome.

Problem Outline

The assumption is that a portfolio of DERs is faced with uncertain forecasts of their available output, as well as of prices on the day-ahead and balancing market. The portfolio operator wants to determine a set of offers to be submitted at the day-ahead market, so that the expected profit of the portfolio is at its maximum, taking into account the exposure to the balancing market in case when the offered quantity is not delivered. Imbalances are assumed to be settled using a pair of cash-out prices – System Buy Price (SBP) for short participants and System Sell Price (SSP) for long participants, as is the case in the UK market.

Price forecasts for the day ahead, both for spot and balancing markets are assumed to be available to the portfolio operator. However, the forecasts contain not only the expected set of prices for all half-hourly periods (as used for settlement in the UK market), but also high and low values for each of the three prices at each time instance, with the corresponding probabilities assigned to these values (normally these probabilities are lower than the one for the central expected value).

By superimposing all possible values of the available capacity of the individual DERs, and possible market prices at a certain time, it is possible to construct a number of combinations, which in the context of stochastic optimisation are called *scenarios*.

The expected profit in each of the scenarios is found as the difference between the expected revenues from the day-ahead market on one side, and expected net payments in the balancing markets and expected generation cost on the other. Offer quantities for the day-ahead market are then sought with respect to the maximum expected profit across all scenarios and their probabilities:

$$\max_{\mathbf{x}} \sum_t \sum_s p_s \left(M_{s,t} x_t + B_{s,t}^S e_{s,t}^+ - B_{s,t}^B e_{s,t}^- - \sum_i C_i g_{i,s,t} \right)$$

where x_t is the offered quantity at time t, $e_{s,t}^+$ and $e_{s,t}^-$ are energy surplus and shortage, respectively, and $g_{i,s,t}$ is the output of generator i at time t in scenario s. $M_{s,t}$ is the day-ahead market price, and $B_{s,t}^S$ and $B_{s,t}^B$ are imbalance prices (SSP and SBP) at time t in scenario s; C_i is the generation cost of generator i.

Individual generator outputs are bounded by their available capacity in each scenario:

$$g_{i,s,t} \le G_{i,s} \ \ \forall t$$

Energy surplus, shortage, contracted quantity and generator outputs in each time interval and in each scenario are linked by the following energy balance constraints:

$$e_{s,t}^+ - e_{s,t}^- = \sum_i g_{i,s,t} - x_t \ \ \forall s$$

As outlined above, the solution for x_t then suggests the optimal quantity to be offered at the day-ahead market with respect to maximum expected profit across all possible realisations of uncertain events. In a general case, this set of half-hourly values will differ from the values that would be obtained by simply taking the expected values of available generator capacity and market prices as the basis for decision making.

CASE STUDIES

The approach outlined in the previous section will be demonstrated on three case studies. Case A includes only conventional distributed generators that exhibit uncertainty through the possibility of suffering an outage. In other words, each generator can at the time of delivery be found in one of two states – either fully available or unavailable, with the assigned probabilities.

In Case B, a wind generator is exposed to the day-ahead and balancing markets. The uncertainty of wind output is modelled through several states of available capacity with given probabilities. The variation of the values around the central value is gradually increased towards the end of the scheduling period, which is in line with the fact that wind output forecasts tend to be less reliable for larger lead times.

Finally, Case C represents the combination of A and B, i.e. a portfolio combining both conventional and wind generators. The same values of generator capacities and state probabilities are retained to enable comparison between cases.

Input Data

Values for half-hourly market price series are obtained from the officially published data for the UK market for May 2008 [6], taking into account only working days within that month. Three main series were constructed, one for day-ahead market price, and two for imbalance prices SSP and SBP. Along with the central price forecasts, each price series is accompanied by two additional forecasts – a higher one and a lower one. In a given period during the day it is assumed that the prices will take their central value with probability 0.6, while higher and lower forecasts are each taken with probability 0.2. Figure 1 shows all three price forecasts and their variations.

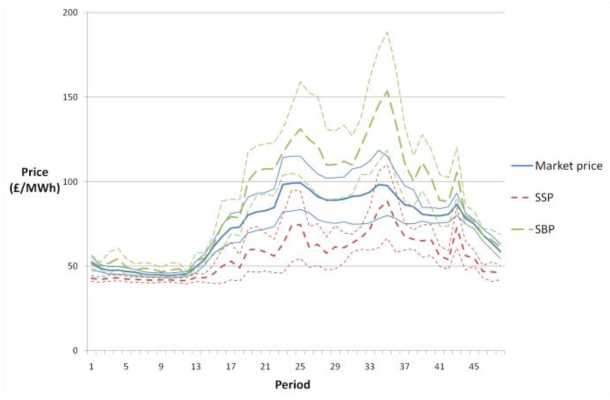

Fig. 1. Forecasts for day-ahead and imbalance prices

Due to the size of the generators considered in this paper, it is assumed that they are price takers, i.e. that they cannot influence the market price through their actions, but only decide whether to sell their output at the market price or not.

The data on the generators for all cases are summarised in Table I. Conventional generators are characterised by their capacity, operating cost and availability, with total capacity of 30 MW. Wind generator, on the other hand, is defined by its capacity probability table, i.e. the likelihood of being able to provide different levels of output. As indicated in the table, the probabilities of some capacity levels change within the scheduling period, implying that the forecasts become less reliable when looking farther in the future. The range of probability values indicated in the table represents the initial and final values, with intermediate values being linearly interpolated.

Table I. Generator characteristics

Case A – Conventional generators			
No.	Capacity (MW)	Gen. cost (£/MWh)	Availability (%)
1	5	50	65
2	10	40	70
3	8	45	55
4	7	48	60

Case B – Wind generator		
No.	Output (MW)	Probability (%)
1	5	5 – 12
2	10	20 – 20
3	15	50 – 36
4	20	20 – 20
5	25	5 – 12

Results

The method described in earlier sections was implemented using a mathematical programming software tool [7]. Optimisation results for all three cases included the optimal offering strategy throughout the day, and the expected profits achieved in the same period.

Figures 2, 3 and 4 show the results for optimal offers and expected profits in the three cases when applying the proposed approach. In each chart the performance of the optimal strategy based on stochastic optimisation is compared to the strategy based purely on expected values of available generator capacity and market prices.

Clearly, when both strategies are exposed to uncertain generator availabilities and market prices, the stochastic strategy consistently outperforms the one based on expectations. This is the result of the fact that the stochastic strategy tends to adapt better to risk profiles encountered in different times of the day, i.e. to uncertainty of day-ahead and imbalance prices.

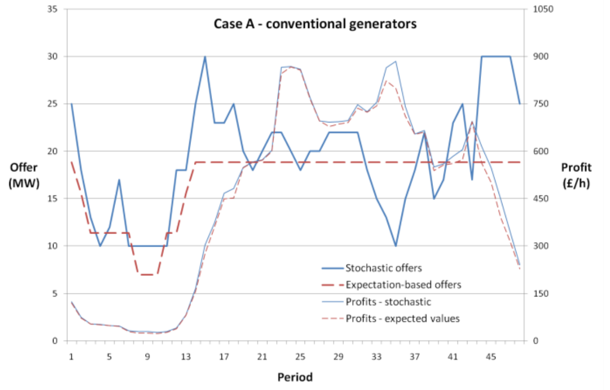

Fig. 2. Offers and expected profits for Case A

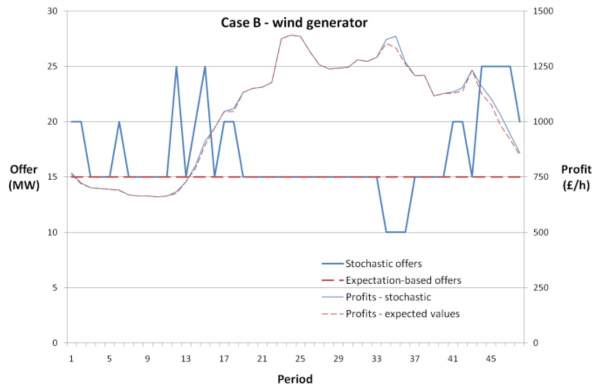

Fig. 3. Offers and expected profits for Case B

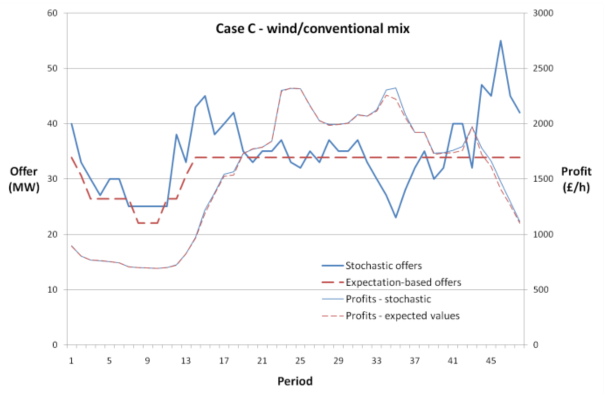

Fig. 4. Offers and expected profits for Case C

The adaptability of the stochastic approach can best be seen by looking at several specific times of day. For instance, in periods 34-36 the profile of imbalance prices is significantly skewed towards higher price levels. This is recognised by the stochastic strategy through offering less quantity at the market to reduce risk of paying excessive System Buy Prices. On the other hand, towards the end of the scheduling horizon (periods 44-47) there is an opposite effect, i.e. the imbalance prices are skewed towards lower price levels. The stochastic strategy responds to that accordingly by offering more energy than is expected to be available, in order to reduce exposure to the risk of receiving very low System Sell Prices.

Table II summarises the total daily profits for both stochastic and expectation-based strategy. An important phenomenon is the increase of total expected profit when conventional and wind portfolios are aggregated, compared to the sum of profits of Cases A and B. This aggregation benefit occurs both for the stochastic-based and expectation-based strategy, implying that significant synergic effects can be achieved by aggregating wind and conventional generators. This effect comes as the result of increased flexibility in Case C, which allows for internal balancing within the portfolio once the uncertainties regarding the prices and availabilities have been resolved.

Table II. Expected daily profits for different cases

	Total expected daily profit (£)		
	Stochastic offers	Expectation-based offers	Difference
Case A	22,146	21,510	636
Case B	49,981	49,674	307
Case C	73,871	73,158	713
Aggregation benefit (C−A+B)	1,744	1,974	-

The improvement after applying the stochastic strategy instead of the expectation-based one varies between 0.6% (Case B) and 3% (Case A), while in the combined case this value is around 1%. Gains achieved from aggregating conventional and wind portfolios amount to 2.4% of the arithmetic sum of profits in Cases A and B.

Table II also implies that the aggregation brings larger benefits when expectation-based strategy is used, than is the case with the stochastic approach. An explanation for that could be that the starting position for the expectation-based case is farther from optimal policy in Cases A and B, and therefore the added flexibility introduced in Case C brings even more additional value than with stochastic-based policies. The total level of expected profits is still considerably higher in case when stochastic strategy is used.

CONCLUSION

This paper provides a description of a model that can be used to determine the optimal strategy of offering electricity at the day-ahead market for a portfolio of DERs. The model incorporates the stochastic nature of the problem by taking into account uncertainty of generator output and forecasts of day-ahead and imbalance prices. The results show how the proposed approach is able to adapt the strategy to the risk profile that the portfolio is exposed to in different times of the day. Furthermore, it is demonstrated that significant synergic effects can be achieved by aggregating wind and conventional generators into a single portfolio. This is a consequence of increased flexibility in performing intra-day internal portfolio balancing, thus reducing exposure to imbalance prices.

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