

Aspects of Wind Energy Characteristics in Transmission Related Optimisation Models

Invited Panel Discussion Paper

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Abstract—This invited panel paper discussion will outline a number of aspects of wind energy characteristics relevant to the optimal wind/transmission model formulation task. Optimal placement of wind capacity on a constrained transmission network is a typical example of this type of problem. In particular the relevance of advanced and computationally intensive stochastic unit commitment to the model formulation will be debated. Optimization constraint matrix structure and techniques to exploit it will be shown to be of considerable importance for this type of problem. The relative merits of different model dimensionality reduction schemes, either through multivariate component analysis and probability discretisation or indeed scenario reduction, will be discussed. A pragmatic acceptance of the imprecise impact of long-term power system uncertainties will be maintained throughout, and wherever possible generality to different types of power systems will be considered.

Index Terms—power system planning, power transmission, wind energy.

I. INTRODUCTION

Wind energy is considered as a promising source of alternative power generation in many electricity systems at this present time [1]. Not only is it renewable and therefore environmentally friendly, it is also indigenous to the power systems where it is developed, and thus contributes to national energy-mix security-of-supply [2]. The distinctive characteristics of wind energy, when compared to more traditional conventional power generation sources, have significant modeling implications for transmission related optimization problems however. The extent to which wind power characteristics (with low capacity factor, low capacity credit, geographically interdependent generation patterns and associated variability and forecast uncertainty) require modification of transmission planning methods and assumptions is a key question for many power system planning engineers around the world.

Traditional transmission planning analyses were more

deterministic in nature, focusing on the network's capability at particular 'snapshot' conditions such as the 'winter-day-peak' or the 'summer-night-valley' for example – conservative studies of system performance in these onerous cases then generally encapsulated the extremities of normal power flow behaviour to be expected over the much broader set of more typical daily and seasonal operating conditions. The variable and statistically inter-dependent nature of spatially distributed wind generation power production, as well as its weak load-following characteristics, implies that a much greater combination of power flow contributory conditions is now possible, and therefore system study over a more diverse set of cases must be considered. This necessity will have unavoidable dimensionality consequences for transmission system study formulations – associated transmission-related optimization problems will thus be much larger in scale. Year-long 8760-hour time series power flows are now becoming common in power system analyses with wind energy connection for example [3],[4]. The emergence of advanced stochastic unit commitment and dispatch methods to deal with operational wind variability and uncertainty [5],[6] is also of potential interest to the optimal transmission planning modeling problem. Whether the significant complexity associated with such operational timeframe scheduling tools is relevant in the longer term transmission planning task is also a necessary issue to consider at the problem modeling stage.

In any case, transmission planning and related tasks should be framed within the context of long term power system requirements and characteristics, as network infrastructural developments often have a lifetime measured in decades. The uncertainty associated with future system power flow requirements (e.g. due to load profile shapes, fuel prices, generation plant locations etc) over this time horizon should also be acknowledged when deciding on the precision of any optimal planning model formulation. Techniques and pragmatic assumptions that minimize the study dimensionality and complexity, while preserving a reasonably good representation of the stochastic wind power behaviour will be of significant utility in many applications.

This invited panel paper will report on the main aspects and results of various research analyses contained in [7] that relate to this optimal wind/transmission planning modeling task. Iterative production costing simulation is usually an important element or sub-task in the solution of this type of problem [7]. Key aspects of the discussion will therefore focus in particular on:

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- the relevance of whether to include advanced stochastic mixed-integer unit commitment tools within the optimal transmission planning model
- the importance of maintaining a pragmatic understanding of the impact of long term power system uncertainties relative to other modeling concerns
- the large scale of the optimization models that generally result and possible ways to take advantage of any constraint matrix structure
- various techniques that are useful in optimization model dimensionality reduction, both in the spatial sense (with multivariate component analysis) and the temporal sense (with scenario reduction)

The relatively simple test system upon which these studies were performed is initially outlined in Section II. An overview of the methodologies and a summary of the main results and discussion points of these different studies listed above will be presented in the subsequent sections of this panel paper.

II. TEST POWER SYSTEM

The test system used in the analyses of this paper is illustrated in Fig.1. This has a 35-bus, 54-line network, denoted as ‘Area 1’ (based on a rather simplified model of the Irish ‘All-Island’ 220/275/400KV high-voltage transmission system). A DC-power-flow security constrained optimal power flow (SCOPF) model was applied where relevant in this paper, with any single generation or network outage assumed as the N-1 security criteria. It contains a mixture of base-load and mid-merit fossil-fuel (coal and peat) steam turbine generation, combined-heat-and-power gas plants (CHP), combined-cycle gas turbines (CCGTs), higher-efficiency aero-derivative gas turbines (ADGTs), lower-efficiency open-cycle gas turbines (OCGTs), as well as a few gas/oil-distillate ‘peaking’ units, amounting to 10.4GW conventional plant capacity overall. 500MW of HVDC interconnection capacity to a much larger separate power system denoted as ‘Area 2’ (based on an approximate model of the Great Britain generation portfolio) is available at both buses 12 and 34, denoted as ‘IC-1’ and ‘IC-2’ in Fig.1. Conventional plants in Area 2 are grouped approximately into multiple generation capacity blocks of similar plant-type, all connected at a single transmission node. System conventional plant performance data, seasonal natural gas fuel price variations, load profile, load magnitude (accounting for projected Area 1 load growth to a maximum peak value of 9.61GW), and the assumed load geographic distribution are consistent with [8]. Load profile information for Area 2 was sourced from [9]. Additional information on the test network branch reactance and thermal capacity parameters, the assumed system geographical load spread, and the conventional generation portfolio network locations and base-case fossil fuel costs as applied in this investigation are available in the appendix of [7].

Synchronously recorded historical load demand and wind power data from multiple geographically distributed existing wind farms on the Irish power system was used for the studies reported in this panel paper. Usefully, these historical wind

time series will inherently represent both the characteristics of the wind resource at each individual site as well as any multivariate spatial power output dependencies between geographically distinct regions, and indeed any weaker dependencies between the wind and load demand profiles. Though if historical data is used directly then possible inter-yearly wind profile variations should also be expected and accounted for [10],[11].

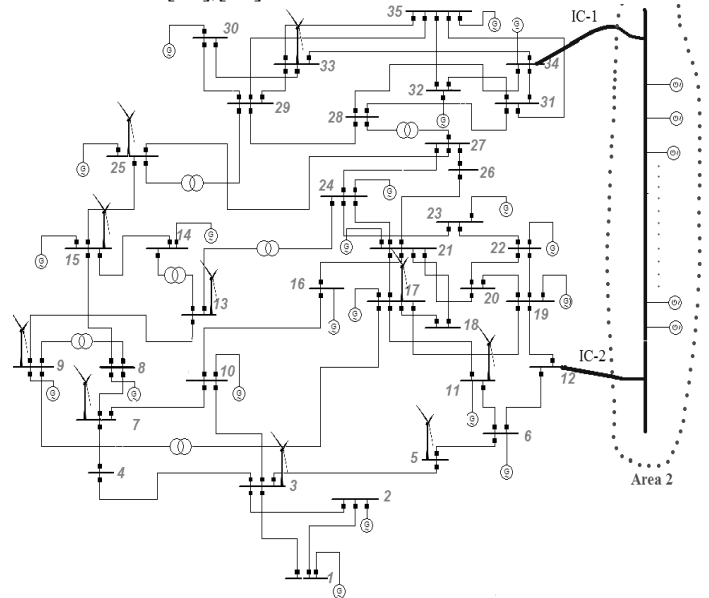


Fig.1 – the test power system under investigation [7].

III. LONG TERM POWER SYSTEM UNCERTAINTY IMPACTS

The formulation of the long term system planning problem is significantly impacted by model uncertainty. Decisions taken must be somewhat robust to a number of alternative parameter outcomes – such robustness criteria will generally increase the solution cost. Power system demand growth rate predictions are always approximate in nature at best. The future effects of electric vehicle integration, and the envisaged revolution in demand side interaction using smart-metering technology etc, are furthermore significantly uncertain for future demand profiles at this present time. The change in load profile magnitude (or overall electricity demand level) and indeed load profile shape (if electricity use is shifted to different periods of the day) could have an important impact on the transmission network power flows in some power systems. Equally importantly, the volatility related to fossil fuel prices and the potential effects of different carbon dioxide emission prices on conventional generation dispatch costs have uncertain impacts on the generation portfolio merit order. It must be noted that the aspects of a transmission planning model formulation which are most relevant to the decision outcomes (e.g. ‘tail-risk’ events such as network congestion etc) may be most susceptible to these types of uncertainties. The effect of fuel price volatility on the power system dispatch merit order is illustrated in Fig.2 for example. If the gas fuel price is increased or decreased by 25% relative to a base-case assumed value, then the relative merit order position of base-load CCGTs and traditional steam coal would be

interchanged, leading to different power flow patterns over the year in the test power system transmission network, as shown in Fig.3 [7].

What is equally critical to remember of course is that from a decision-making perspective, the relative importance of the ‘base-case’ fuel price scenario and the arbitrarily chosen +/- 25% gas price sensitivities is difficult to ascertain [12]. Sensitivity analysis is often applied for parameters such as fuel price and load profile assumptions in optimization models, but the number of sensitivity scenarios, and their relative importance (or probability-weighting) must generally be subjectively chosen to some extent. When the impact of these vaguely uncertain parameters can sometimes be so influential, and given that the justification for their parameter values is somewhat subjective, then the relative importance of maintaining absolute precision for other transmission network modeling issues must be considered in the correct context [7], as will be discussed in the following paper sections.

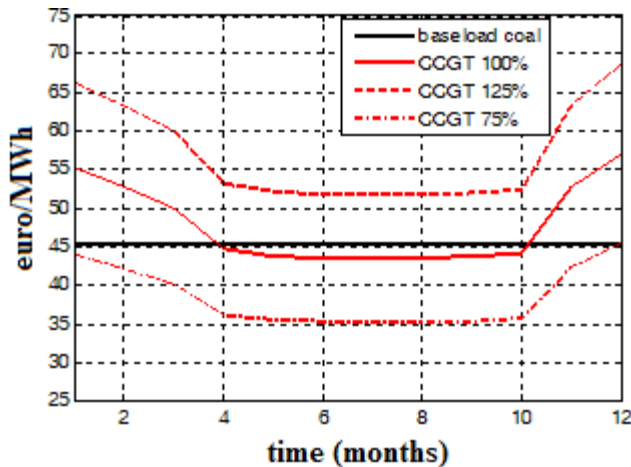


Fig.2 – Seasonal base-load coal and CCGT average unit costs – possible effect of gas fuel price uncertainty.

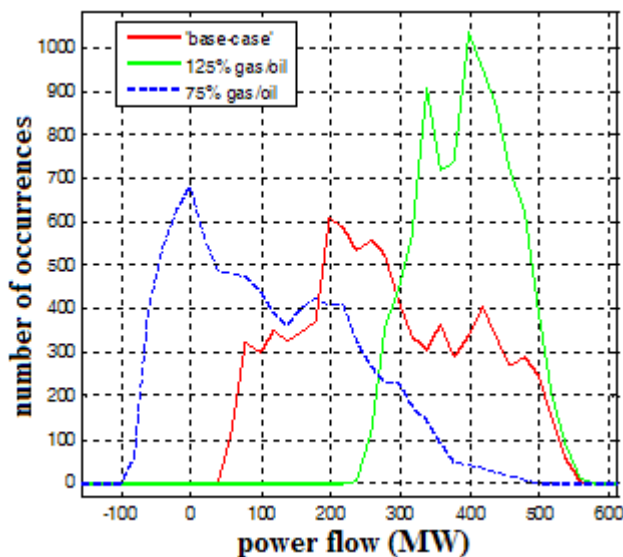


Fig. 3 – sample pdf of yearly line flows under the influence of gas fuel price uncertainty (network line from buses 9-13).

IV. INCLUSION OF OPERATIONAL UNIT COMMITMENT ISSUES

In power systems with significant wind energy penetration levels, conventional plants are likely be scheduled out of simple dispatch merit order from time to time in order to provide sufficient flexibility in the online set of units to respond to wind variability and forecast uncertainty [5],[6] – this effect has been observed in many advanced wind integration studies [8]. The extent to which the transmission network power flows and congestion levels are modified in such advanced mixed-integer stochastic scheduling models with respect to a simpler merit-order dispatch approximation will be relevant to the optimal transmission planning modeling effort. If the difference in power flow modeling is not so significant, then the large computational burden associated with the advanced scheduling approaches could be determined as un-necessarily excessive, particularly in the light of the arguments outlined in Section III.

An advanced scheduling tool (WILMAR [5]) was applied to the Fig.1 test power system generation portfolio with different levels of complexity to investigate this issue [7]. The transmission network power flow modeling precision of a full stochastic mixed integer unit-commitment solution (SUC) (i.e. including both wind variability and forecast uncertainty) was compared to both that of a deterministic unit commitment model assuming perfect wind forecasting (DUC-PF) (i.e. modeling wind variability only), and also a very simple merit order based dispatch using linear programming (MO). Transmission power flows will be different across the three models in a small number of network lines adjacent to flexible conventional generation sources and the HVDC interconnection points between Area 1 and Area 2 in Fig.1.

These flexibility sources (e.g. the interconnector) will be mainly used to accommodate operational wind variability and uncertainty challenges. An example of this power flow modeling issue is given in Fig.4, where the probability density function (pdf) of year-long power flows in the line from bus 12-19 (adjacent to the IC-2 connection point) is illustrated for the three system dispatch model choices. Clearly there are some power flow modeling (and therefore transmission planning) implications of the operational unit commitment issue in systems with significant wind penetration. However, aside from this small number of lines, there was little difference in the yearly power flows in the other parts of the transmission system, as representatively illustrated with the line flow pdf comparisons in Fig.5. The relative importance of operational-timeframe wind variability modeling, when compared to the pragmatic discussion of other uncertainties in Section III, thus should be considered in the transmission planning model formulation, especially when its computational burden is so significant (approx. 36 hours for a year-long mixed-integer stochastic unit commitment study for the test power system, with a duality gap of 1% [6]). The only part of the wind/transmission optimization model formulation for this test system where it might be genuinely required to model SUC issues would be any HVDC interconnection

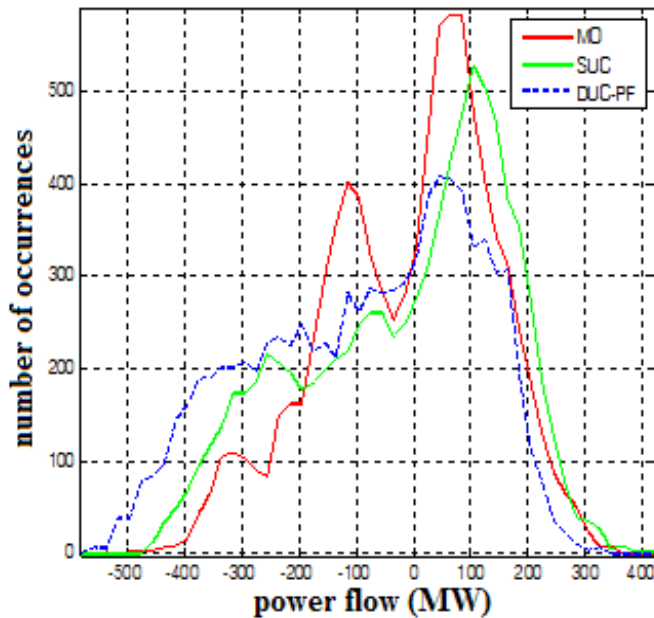


Fig.4 – yearly power flow histograms for line adjacent to HVDC interconnection point to Area 2 (line 12-19).

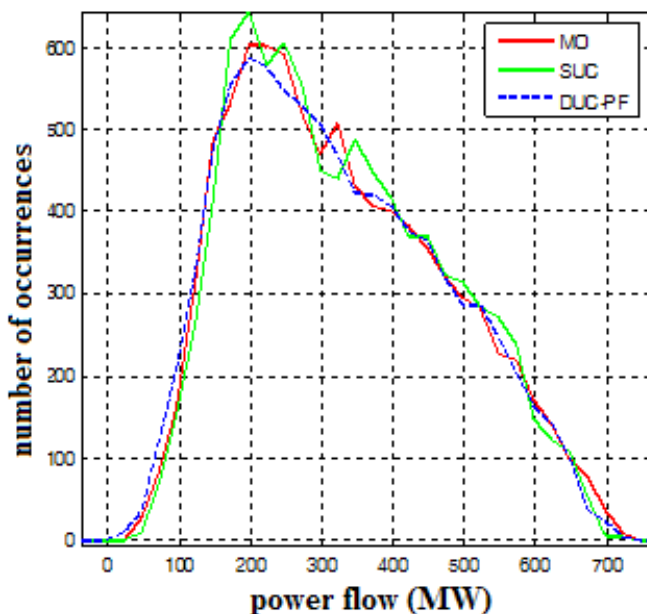


Fig.5 – sample yearly power flow histogram from elsewhere in the system (e.g. line 17-21).

re-enforcement decisions between Area 1 and Area 2, as these inter-area power flows will be most affected by the choice of operational wind power management model to apply.

In general though, the additional precision obtained may not be so valuable when compared to the longer-term pragmatic uncertainties and the associated computational burden in many power systems. If stochastic unit-commitment issues can be justifiably disregarded, then the optimal transmission planning model formulation task is significantly simplified – the unit commitment integer variables can be relaxed and replaced by a much simpler linear programming based merit-order dispatch approximation.

V. CONSTRAINT MATRIX STRUCTURAL CHARACTERISTICS

Optimization problems related to wind power and transmission system networks will be inevitably larger in size than those experienced with traditional conventional generation in the past [13], mainly due to the greater diversity in transmission load flow situations with many geographically dispersed yet somewhat statistically-dependent wind power generation sources. A specific example of this situation is given in the optimal non-firm wind capacity placement problem in a congested network [10]. Like all large scale optimization problems however, there is generally some ordered structure in the constraint matrix that can be exploited by an effective solution scheme. ‘Investment’ timeframe and ‘operational’ timeframe variables are often separable for example, with important problem tractability consequences.

For example if historical time series [10],[14] or indeed synthetically generated sample data [15] is used to represent wind power statistical behaviour in the transmission network constrained generation production-costing simulation model, then there will be one separable hourly security-constrained optimal power flow problem (SCOPF) that each makes up a distinct block of the constraint matrix. If the investment decision variables (e.g. network topology or generation capacity investment location etc, which may also be integer in nature) are iteratively fixed in a master problem solution process, then these operational sub-problems can be solved separately with traditional Benders’ decomposition schemes [10] as depicted in Fig.6 and Fig.7. Decomposition schemes are generally computationally intensive, though at least they will make the problems tractable. In addition, decomposition schemes are often parallelizable, depending on the number of separate computer processors available.

If there is significant energy-limited storage capacity (e.g. pumped-hydro) in the power system generation portfolio, then the division of the constraint matrix into fully separable hours is not possible though, as each hour will depend on the storage state of the last, and furthermore will condition the storage state of the next. In this case a nested-decomposition scheme [16] may be necessary as the constraint matrix may have a staircase-structure instead of the block-diagonal structure in Fig.6. Nested decomposition schemes can be more computationally intensive to implement.

The presence of large amounts of such storage capacity may therefore significantly complicate the model formulation and solution process for optimal wind/transmission problems. Certain model compression approaches also may not be possible if the link between hours cannot be justifiably disregarded, as will be outlined in Sections VI and VII. On the other hand though, some studies have shown that the addition of even relatively significant amounts of wind power to the system may not significantly modify the optimal operating pattern of the storage units (pumping at night time system load minimum levels and generating at the daily system peak) [17] – the relevance of such results to optimal wind/transmission model formulation may be more clear with additional future research.

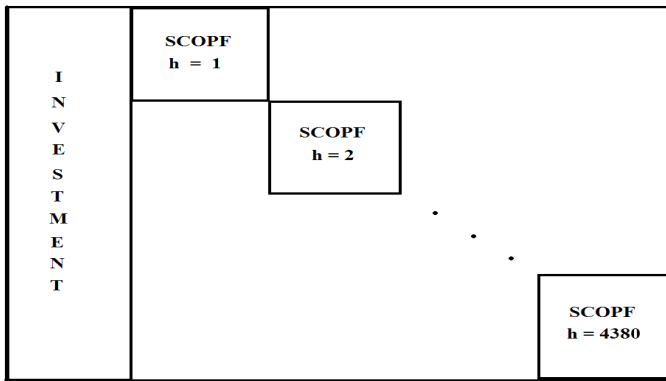


Fig.6 – block diagonal constraint matrix structure [7],[10].

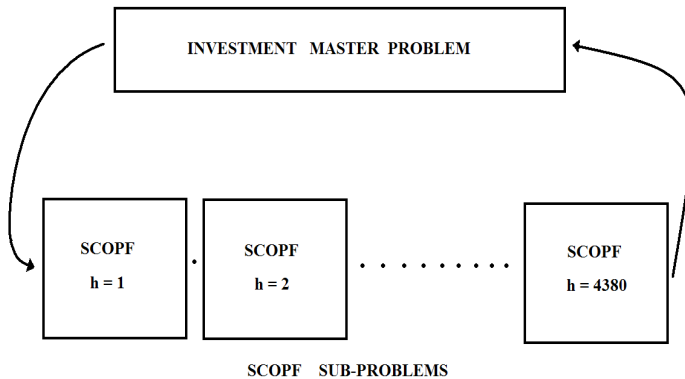


Fig.7 – Master/sub-problem Benders' decomposition scheme [7],[10].

VI. SPATIAL MODEL COMPRESSION USING MULTIVARIATE COMPONENT ANALYSIS

The spatial separation of each wind farm in geographically different areas means that the power production from each wind farm will have distinct statistical characteristics. In a power system area of appreciable size, this could lead to hundreds of distinct random statistical variables, which could be unwieldy for model descriptive purposes. A straightforward approach would suggest the grouping of geographically close-by wind farms to single representative zonal variables such as in [18]. The relationship between these zonal variables will still have a lot of statistical dependency though, and therefore statistical model redundancy – it would be useful if a more rigorous statistical dimension reduction scheme could be determined.

Representation of wind statistical behaviour using 8760-hour time series sampling in the optimization model structure of Fig.6 leads to a significant computational burden in performing the sub-problem routines for each iteration of a Benders' decomposition scheme. If a lower number of discrete cases could be determined that adequately represents the multivariate wind statistical behaviour, then significant model compression and therefore computational efficiency could result. The accuracy degradation of any model compression approaches must be carefully considered with respect to the intended model application of course – for long term system planning purposes with many other vague parameter uncertainties, significant model approximations may be allowable, but this might not be prudent for precision

reliability assessment of a present power system configuration.

A basic approach to reducing the number of representative SCOPF cases could go as follows [19],[20]. For the two-wind farm bi-variate scatter plot in Fig.8, dividing each marginal statistical variable into an arbitrary 10 discrete regions would lead to $10 \times 10 = 100$ possible combinations of bivariate discrete cases (or 100 two-dimensional histogram bins, assuming binning density of 10 for each individual variable) that describe the statistical dependency quite well, with each discrete bin probability-weighted or scaled by the number of the hourly historical observations contained within it. The drawback with this basic probability discretisation approach is of course that if a third wind farm region was added, there could conceivably be up to $10 \times 10 \times 10 = 1000$ discrete cases, and exponentially so on for each additional distinct wind region. A method that describes the multivariate dependency of a large number of spatially separate statistical wind regions with a much lower number of statistical variables, and that can furthermore reduce the binning density to a lower number than 10 for each marginal variable, could be of more practical use.

Principal component analysis (PCA) [21] is a statistical transform technique that uses eigenvalue/eigenvector analysis of the distributed wind covariance matrix to project the original set of random variables to an arbitrarily lower dimensional set of alternative variables (called the 'principal components'). Furthermore the principal components are statistically uncorrelated (though for non-Gaussian multivariate random variables such as the distributed wind power case, it must be noted that this is not quite the same as statistical independence [15]). Equally relevant is the fact that if the eigenvalues associated with each respective component are significantly different in magnitude, then some of the corresponding principal components can be interpreted as being more important than others to be retained in the transition to the lower dimension multivariate set. Each additional principal component basically explains a progressively lesser amount of the variance of the original variables. Only the first few components might be retained if there is a high degree of correlation in the original set of wind power statistical variables. The eigenvalues resulting from a PCA study [7], [22] of distributed wind power data from 9 distinct wind regions in the Irish power system are illustrated in Fig.9. Clearly the first 3 or 4 components explain the most of the variance in the original 9 zonal wind power variables, and the remaining higher order components might be justifiably discarded. The fact that the retained components/eigenvalues are different in magnitude is also relevant to the choice of binning density if a probability discretisation approach was applied to the transformed component set instead of the original variables in Fig.8 – if 10 bins was required for the 1st component, then 5 or 3 bins might be allowable for the other remaining ones – less combinations are thus needed in this case.

So the benefit of the PCA approach with the reduction in the number of variables (statistical dimensions), the

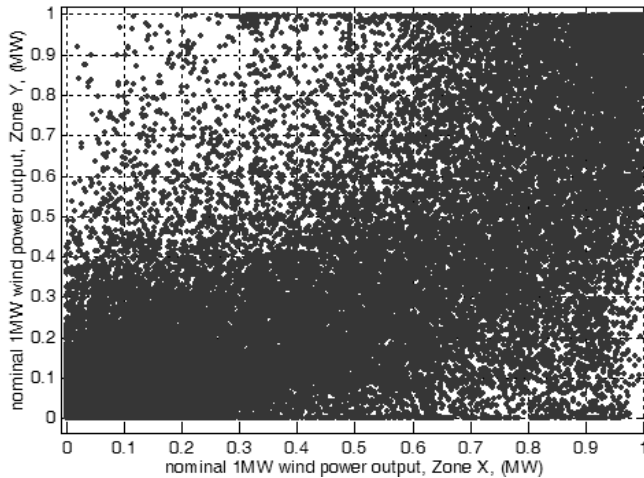


Fig.8 – Scatter plot of nominal wind power output for Zones X, Y [7], [22].

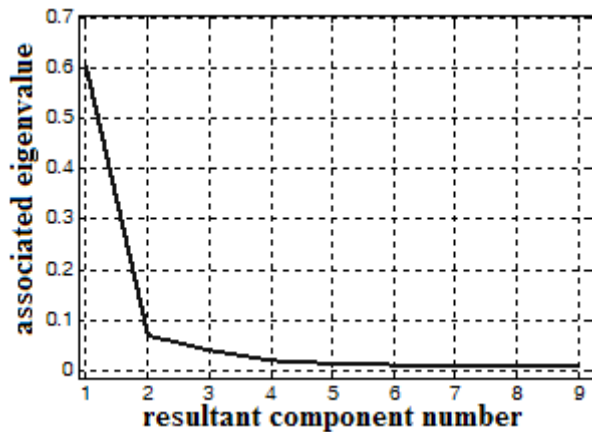


Fig.9 – Ordered eigenvalue plot associated with each principal component – Irish wind power regime [7], [22].

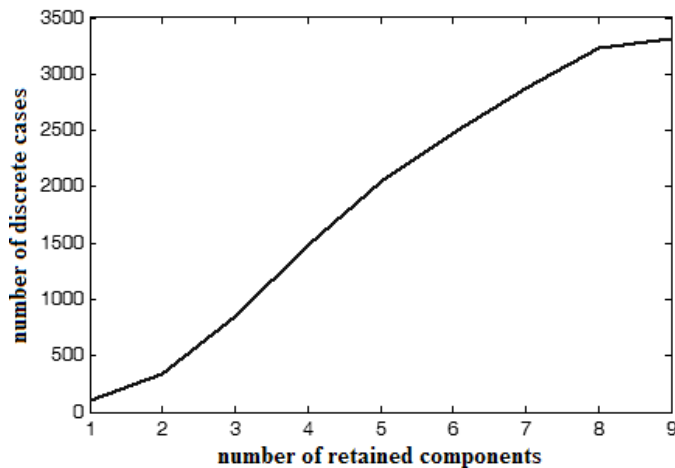


Fig.10 – The number of probability-weighted discrete cases for different numbers of retained components in Fig.9– [7], [22].

discretisation or ‘binning’ densities of which are furthermore tailored with respect to the associated eigenvalue, is that a lower number of probability-weighted discrete cases might represent the original 8760 hour multivariate time series quite well. A lower number of distinct power flow cases means less sub-problems to be evaluated in optimization decomposition schemes for example [10], as typically indicated in Fig.10 [22]. The utility of the PCA and subsequent probability

discretisation approach will depend on how few components can be justifiably retained while maintaining appreciable accuracy, and therefore how correlated the original wind power variables are – it may thus be mainly suitable for small to medium sized geographical regions. Equally important is the clarification that this combination of sequentially non-related hours in a binning and discretisation procedure relies on the assumption that there is little or no energy-limited storage capacity in the power system portfolio – as discussed in Section V, such an assumption might not be allowable in some power systems.

VII. TEMPORAL MODELING COMPRESSION USING SCENARIO REDUCTION

The efficiency of the PCA and subsequent multivariate probability discretisation process will mainly depend on whether a relatively low number of retained components can adequately describe the original wind power marginal statistics and multivariate dependencies. Alternative approaches may be required in geographically larger power systems, where the correlation between distributed sites is not so strong, and therefore the relative importance of the first few eigenvalues is not as profound compared to Fig.9. If the sequential hour to hour dependencies of the wind power time series sample data can be relaxed, as discussed in Section V, then similar hourly cases across the whole length of the time series data can perhaps be combined as one representative case with a combined resultant probability weighting. The scenario reduction process [23], [24] is such an alternative scheme to achieve this.

Scenario reduction methods are often used to reduce the computational dimensionality of optimization problems to a more tractable level. They are non-parametric and do not rely on any particular dependence structure between multivariate statistical variables. For example scenarios are often applied to efficiently describe uncertainty in intra-day operational wind power, load demand or electricity price forecast stochastic variables [5],[24]. In the optimal wind power and transmission planning process context, then instead it is the actual distributed wind power productions over a yearly timeframe that are the stochastic variables of interest. In this particular problem case, the equally-weighted hourly time series of recorded multivariate wind data samples can be considered as the initial set of scenarios, which is then reduced in cardinality to an arbitrarily lower dimensional probability-weighted group of representative cases [7]. The choice of which scenarios to retain and which to discard is determined by the set that ensures a minimum probability-distance (e.g. the Kantorovich distance [23]) between the retained set and the original full-cardinality set. In contrast to the PCA statistical dimension reduction approach in Section VI however, the same number of random variables is retained in the scenario reduction approach – it is only the number of case-samples describing them that is reduced.

In the work of [7], the ‘simultaneous backward’ scenario reduction scheme of [23] was used to reduce the number of

time series data cases for wind power and transmission optimization problems. A simple illustration of this is given in Fig.11 and Fig.12 below, where the 500 historical data samples from a bivariate wind power dependency are reduced to 100 probability-weighted representative cases.

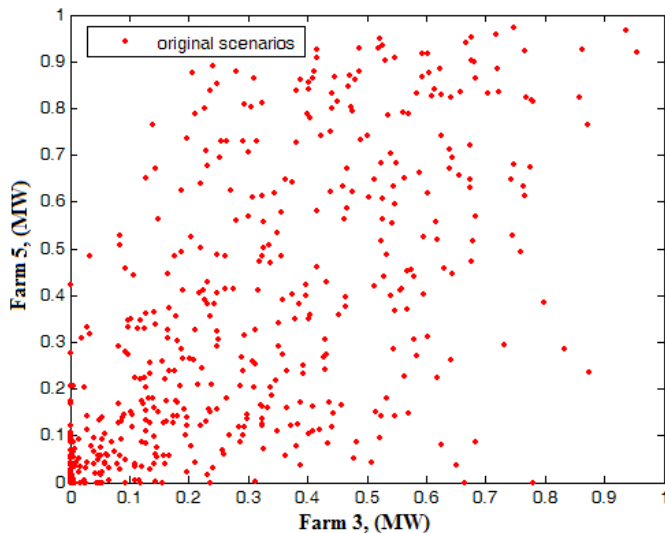


Fig.11 – Bi-variate scatter plot of 500 hourly wind power samples.

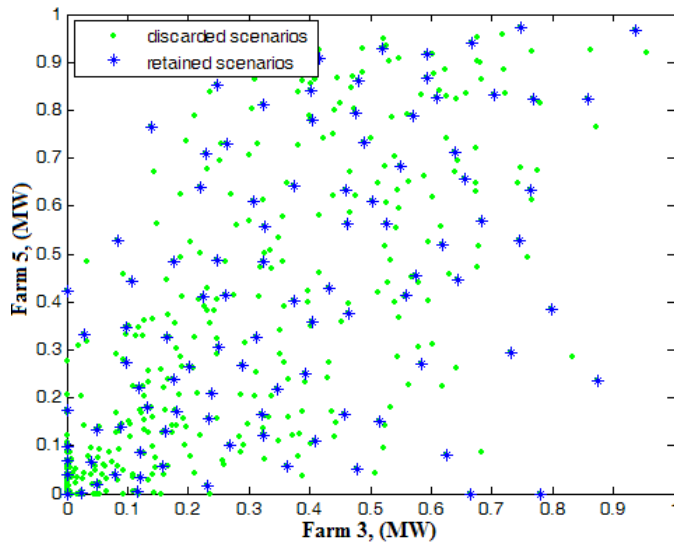


Fig.12 – Effect of scenario reduction – 100 samples retained.

Note how the general spread of the data-point distribution is maintained - data-points that are close-by and therefore redundant are discarded in Fig.12 and their probability allocated to the Euclidean-nearest retained neighbor. It has been shown in [7] how a much lower probability-weighted number (e.g. 400 or so) than one year of 8760 hourly data samples can still give very good results in typical wind/transmission related optimization problems such as in [10], while ensuring that many fewer decomposition sub-problems have to be solved. The computational burden of the optimization problem can thus be reduced by an order of magnitude for little optimal decision variable or optimal cost function degradation. Furthermore, in contrast to the PCA discretisation technique of the previous section, the efficiency is not as directly linked to the geographical size of the power

system, and therefore the scenario reduction approach may be more relevant for efficiently modeling distributed wind energy production in larger sized power transmission systems. Of course model reduction and compression will generally lead to a small loss of precision in every optimization problem, but again, relative to the effects of long-term transmission planning uncertainties as outlined in Section III, then a relatively coarse representation of wind power statistical effects may be allowable in many applications.

VIII. DISCUSSION OUTLINE

This invited panel paper discussion will outline a number of aspects of wind energy characteristics relevant to the optimal wind/transmission model formulation task. In particular the relevance of advanced and computationally intensive stochastic unit commitment to the model formulation will be debated. Optimization constraint matrix structure and techniques to exploit it will be shown to be of considerable importance for this type of problem. The relative merits of different model dimensionality reduction schemes, either through multivariate component analysis and probability discretisation or indeed scenario reduction, will be discussed. A pragmatic acceptance of the imprecise impact of long-term power system uncertainties will be maintained throughout, and wherever possible generality to different types of power systems will be considered.

IX. ACKNOWLEDGEMENTS

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XI. BIOGRAPHIES



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