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A Study of Optimal Non-Firm Wind Capacity Connection to Congested Transmission Systems

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Abstract—As wind is a low capacity factor source of power generation, a non-physically-firm connection strategy is key to its cost-effective and timely integration to presently constrained transmission networks. This paper therefore outlines the design and study of an optimal non-firm wind capacity allocation model. While a precise statistical representation of wind power variations and geographical inter-dependency requires a significant number of data samples, the structured very-large-scale linear programming problem that results is shown to be exploitable by the Benders' decomposition scheme. Various wind capacity target levels are considered, and important sensitivity analyses performed for multiple load profiles, wind profiles, and fuel price parameter values. Interestingly, the optimal wind capacity allocation is found to be reasonably robust to sizeable load and fuel price deviations, and while the effect of a limited historical wind data profile is more influential, the associated cost-function penalty is not significantly critical. The economic value of combining wind connection with advanced post-contingency network remedial action schemes is also highlighted.

Index Terms-- power generation planning, power transmission, wind energy.

I. NOMENCLATURE

A. Indices

- i - network bus index in Area 1.
- k - network bus index in Area 2.
- h - time series hourly index.
- j - Area 1 network branch index.
- g - Area 1 conventional generation index.
- w - Area 1 wind generation index.
- f - Area 2 conventional generation index.
- n - HVDC interconnection line index between Areas 1, 2.
- η - Area 1 network branch contingency index ($\eta=1$ for intact-network).
- ζ - Area 1 generation contingency index.

B. Constants

- ε - wind capacity investment cost, (euro/MW).
- β - generation or HVDC operating cost, (euro/MWh).
- σ - wind capacity connection target for Area 1, (MW).
- P_{MAX} - dispatch variable maximum value, (MW).
- α_{ijn} - DC load flow sensitivity of branch j to power injection at bus i under network contingency scenario η .

- L - network branch thermal power capacity, (MW).
- J - total number of transmission branches in Area 1.
- W - total number of potential wind farms.
- G - total number of Area 1 conventional generators.

C. Time series

- ω_{wh} - nominal 1MW wind power time series for potential wind farm location w , (MW).
- γ_{ih}, γ_{kh} - customer load demand time series, (MW).

D. Optimization Decision Variables

- C_w - wind investment capacity at potential wind site location w , (MW).
- P_{gh} - hourly power generation of conventional plants in Area 1, (MWh).
- P_{wh} - hourly power generation of wind farms in Area 1, (MWh).
- P_{jh} - hourly power generation of conventional plants in Area 2, (MWh).
- P_{nh} - hourly dispatch of HVDC interconnection lines, (MWh).

II. INTRODUCTION

The generation mix of many power systems is currently experiencing a significant transition, with wind power considered to have a key role to play in the evolution of less carbon intensive and more environmentally sustainable electricity supply systems. Transmission network limitations are an almost universal impediment to the rapid deployment of wind capacity needed to satisfy such ambitious renewable energy integration policy targets however [1]. Prudent use of existing transmission assets could be made with an optimal wind capacity allocation strategy, ensuring the most efficient and cost effective integration of wind energy in the short- to medium-term while any necessary long-term transmission expansion is simultaneously in development.

The low capacity factor and low capacity credit [2] of wind generation have important implications for transmission design criteria. Physically-firm transmission connections [3] imply that no curtailment should occur due to network congestion. Post-optimal analysis from [4] however indicates that the provision of completely physically-firm connections for wind generation projects (to guarantee wind power export at all times) will result in a largely over-designed network. A more carefully designed non-physically-firm connection could allow export of most of the annual available wind energy with significantly less infrastructure requirement [5]. A tradeoff between two principle factors will therefore influence the optimal non-firm wind capacity allocation solution for a given power system, namely the relative wind capacity factors in each region, and the network congestion impacts of new generation connection at each respective node. A competent

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optimization model formulation should therefore accurately capture both of these factors in a concise manner.

A chance-constrained, stochastic programming based genetic algorithm is proposed in [6] for the optimal wind-transmission expansion planning problem. The analytical formulation of this approach based on convolution (implying the assumption of independence), may not be ideally suited to the intricate multivariate statistical dependencies that apply to distributed wind production and load demand in reality however. Historical recorded data sampling over extended timeframes is often used to model wind production characteristics in many wind integration studies [1], [4], [7], [8]. A combined wind/conventional-generation optimization placement study was outlined for the British power system in [9], yet limited representation of wind production using a small number of samples and very simplistic modeling of the transmission network are applied. An interesting stochastic-recombining-tree model is proposed to limit wind/conventional generation portfolio optimization problem size while maintaining sequential sample dependence in [10].

The value of including ‘operational’ timeframe sequential issues such as wind variability and forecast uncertainty management within a long-term transmission ‘planning’ timeframe is investigated in [11]. Power flow modeling was only significantly influenced in a small subset of network locations if a stochastic mixed-integer unit commitment solution is retained, particularly when compared to the impact of uncertain long-term demand profiles and conventional fuel price volatility. Therefore the additional precision associated with including stochastic unit commitment within the optimal wind capacity deployment problem may not justify the almost intractable associated computational burden for network optimization studies in many power systems. While optimization problems based on extensive wind profile time series sampling and relatively simpler operational models will still be of considerable size, large scale problems often have suitable structure which can be exploited by an optimization decomposition scheme.

Overall wind integration targets are generally defined on a policy basis [12], or perhaps from a generation-mix portfolio analysis [13]. This paper considers the subsequent medium-term transmission planning task of deciding where to optimally allocate this fixed quantity of non-firm wind capacity on a given network. Extensive sensitivity analysis of the problem solution is performed for multiple wind capacity connection targets, different fuel price and customer demand levels, as well as inter-yearly wind profile variations. The economic and policy-advancing value of wide area remedial action schemes for post-contingency rather than pre-contingency optimal power flow management is also highlighted. The test system is presented in Section III, followed by the linear programming optimization model formulation and sensitivity analysis descriptions in Sections IV and V. Results, discussions and conclusions are given in Sections VI, VII and VIII respectively.

III. 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 very simplified model of the Irish ‘All-Island’ 220/275/400KV high-voltage transmission system). 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 [7]. Load profile information for Area 2 was sourced from [14]. Additional information on the test network branch reactance and thermal capacity parameters (chosen so that no congestion occurs at the zero wind integration level), the assumed system geographical load spread, and the conventional generation portfolio network locations as applied in this investigation are available in [11].

Synchronously recorded historical wind power data from 10 geographically distributed existing wind farms on the Irish power system was used for this study. This data was taken at eight-hourly sampling resolution over a time period of four years (from 2005-2008), giving 4380 time series samples overall. This multivariate power output data was linearly re-scaled to nominal 1MW wind capacity profiles ω_w for the optimisation formulation of Section IV. Usefully, these

Fig.1 – the test power system under investigation.

nominal wind time series will inherently represent both the quality of the wind resource at each individual site, as well as any multivariate spatial power output dependencies between geographically distinct regions. Capacity factor details are given in Table-I, Section V. Optimal non-firm wind capacity connection to Area 1 buses 3, 5, 7, 9, 11, 13, 15, 17, 25 and 33 was investigated, for a number of different total wind capacity connection targets. Wind capacity installation in Area 2 was assumed zero – the performance of the optimal non-firm wind capacity allocation model in Area 1 is of primary interest. All model development for this paper was carried out in MATLAB [15] and GAMS [16], using the MATLAB/GAMS interface available at [17].

IV. OPTIMAL NON-FIRM WIND ALLOCATION METHODOLOGY

A. Linear Programming Model Formulation

The optimal non-firm wind capacity allocation problem, fully outlined by equations (1)-(5), consists of both investment and operational timeframe decisions. As the Area 1 total wind capacity target level σ is assumed to be predetermined and fixed with the equality constraint of (2a), therefore the turbine capacity investment costs ε (furthermore assumed equal for each potential wind plant location) will have no impact on the capacity allocation choice and can be defined zero in the optimization cost function (1). The effect of the problem cost function is therefore to determine the optimal wind capacity allocations so that the overall conventional plant fuel cost for Areas 1 and 2 is minimized over the time series of interest. Wind energy dispatch and HVDC interconnection operating marginal costs β_w and β_n are also assumed zero. Conventional plants in Areas 1 and 2 are modeled in a simple manner using single cost energy bids β_g , β_f . Separate load balance equality constraints (3a) and (3b) apply for each area and each hour of the time series, with the HVDC decision variable flow polarities defined as sources on Area 1 and sinks on Area 2. The HVDC interconnection transfers between Areas 1 and 2 are assumed lossless. Generation dispatch and HVDC interconnection flow transfers are constrained between minimum and maximum nameplate capabilities with inequalities (4a), (4b) and (4c). The product of the wind capacity decision variables C_w and nominal 1MW wind time series profiles ω_w ensures that wind dispatch in any hour h cannot exceed the available resource for each potential location (4d).

The transmission network thermal limitations are enforced in each branch, for each hour of the time series, with inequalities (5a) and (5b). A lossless linear DC load flow model [18] is applied to the transmission network. A DC network model is sufficient for the sensitivity analyses context of this paper, though in reality the impacts of induction-generator wind capacity on steady-state voltage, network stability, fault current issues etc are also of considerable importance [2], and would require detailed post-optimal simulations to ensure acceptable system performance is maintained following wind capacity addition. An “N-1”

security constrained DC optimal power flow (SCOPF) model is applied with any separate single generation or network contingency covered.

The relevant DC power flow power-transfer distribution-factor coefficients will obviously depend on the contingency-state of the network. For the intact-network operational state (hence denoted as $\eta=1$), and each possible single branch security-outage state (i.e. denoted as $(\eta=2, \dots, J+1)$, with the effect of the branch network-path open-circuited and its’ impedance was set to a near-infinite number), the relevant set of linear coefficients $a_{ij\eta}$ of power flow sensitivity on line j to power injection at bus i were computed and stored. These are then used in constraint (5a) to scale the respective Area 1 nodal demand (γ), conventional and/or wind generation (P_g, P_w), and HVDC power injections (P_n), so that the other branch thermal limits L_j are maintained in either positive or negative flow direction for each line j in each hour h of the time series.

The effects of generation contingencies on the power flow security constraints are implied by inequality (5b), whereby the power flow impact of tripping each Area 1 generator in turn, indexed as ζ ($\zeta = 1, \dots, (G+W)$), from the network is modeled for each line j at each hour h of the time series. As branch and generation contingencies are considered separately and not coincidentally (i.e. “N-1” security where $N = (G+W+J)$), then the DC power-transfer distribution-factor coefficients used for each branch in (5b) correspond to those from the intact network contingency state $a_{ij(\eta=1)}$. The total wind capacity allocated to any one transmission node in a real power system would likely be the sum of many individual wind installations, some of which might possibly be distribution-connected. For the sake of realism, then the wind generation outage security contingencies in this paper are not modeled as if caused by the full wind capacity allocation at each node tripping all at the one time, but more realistically as a fraction of the overall nodal allocation C_w . In this model, the optimal wind capacity allocation to each transmission node was (arbitrarily) assumed to be distributed amongst 4 separate farms, and thus only 25% of each wind-generator variable’s dispatch in any hour is considered as its power flow generation contingency level.

All of the optimal non-firm wind capacity allocation problem decision variables and constraints are linear (C_w are the wind capacity investment decision variables that span the whole time series, and $P_{wh}, P_{gh}, P_{nh}, P_{fh}$ are the respective sets of hourly generation dispatch decision variables), so linear programming can be tasked with solution.

$$\text{Cost} = \text{Min} \left\{ \sum_{i,w} \varepsilon_{w_i} \cdot C_{w_i} + \sum_{h,i} \left(\sum_g \beta_{g_i} \cdot P_{g_i h} + \sum_w \beta_{w_i} \cdot P_{w_i h} \right) + \sum_{h,i,k} \left(\sum_n \beta_{n_{ik}} \cdot P_{n_{ik} h} + \sum_f \beta_{f_k} \cdot P_{f_k h} \right) \right\} \quad (1)$$

$$\sum_{i,w} C_{w_i} = \sigma \quad (2a)$$

$$0 \leq C_{w_i} \quad \forall_{w,i} \quad (2b)$$

$$\sum_{i,k} (\sum_g P_{g_i,h} + \sum_w P_{w_i,h} + \sum_n P_{n_{ik},h}) = \sum_i \gamma_{ih} \quad \forall_h \quad (3a)$$

$$\sum_{k,f} P_{f_k,h} - \sum_{i,k} P_{n_{ik},h} = \sum_k \gamma_{kh} \quad \forall_h \quad (3b)$$

$$0 \leq P_{g_i,h} \leq P_{MAX_{g_i}} \quad \forall_{i,g,h} \quad (4a)$$

$$0 \leq P_{f_k,h} \leq P_{MAX_{f_k}} \quad \forall_{k,f,h} \quad (4b)$$

$$-P_{MAX_{n_{ik}}} \leq P_{n_{ik},h} \leq P_{MAX_{n_{ik}}} \quad \forall_{k,i,n,h} \quad (4c)$$

$$0 \leq P_{w_i,h} \leq \omega_{w_i,h} \cdot C_{w_i} \quad \forall_{i,w,h} \quad (4d)$$

$$-L_j \leq \sum_{\substack{i,k,n \\ g,w,n}} \alpha_{ij(\eta)} (P_{g_i,h} + P_{w_i,h} + P_{n_{ik},h} - \gamma_{ih}) \leq L_j \quad \forall_{j,\eta,h} \quad (5a)$$

$$-L_j \leq \sum_{\substack{i,k,n \\ (g,w) \neq \zeta}} \alpha_{ij(\eta=1)} (P_{g_i,h} + P_{w_i,h} + P_{n_{ik},h} - \gamma_{ih}) \leq L_j \quad \forall_{j,h}, \forall_{(g,w) \neq \zeta} \quad (5b)$$

B. Model Decomposition and Solution

A reasonably large number of historical time series samples h may be required to accurately recreate the wind capacity factor and multivariate statistical inter-dependencies in (1)-(5). Therefore even if only the most relevant SCOPF contingencies are included for each branch over each hour of the 4380-sample time series (acceptable due to the localized network impact of most contingencies), a large number of constraints and variables will still result. For the small test system of Fig.1, a direct solution attempt of (1)-(5) would imply $\sim \{98 \cdot 4380 + 10\}$ optimization variables and $\sim \{1988 \cdot 4380 + 2\}$ constraints.

Like most large scale optimization problems however, the optimal non-firm wind capacity placement problem of (1)-(5) has significant structure in its constraint matrix. For example, given that the operational timeframe issues linking individual hours can be ignored without significantly impacting modeling accuracy (as was examined for the stochastic unit commitment issue with this test system in [11]), then the optimal non-firm wind capacity placement problem constraint matrix exhibits block diagonal separability between wind capacity investment and system dispatch operational variables, as illustrated in Fig.2. This can be exploited by the Benders' decomposition scheme [19] - by iteratively fixing the investment variables C_w , the much smaller hourly time series SCOPF problems can be solved separately, as depicted in Fig.3.

From an initial wind capacity allocation solution guess, linear programming dual information from the sub-problems (which give an upper-bound on the optimal cost function value) is used to generate successive feasibility and optimality cuts for the investment master problem (which gives a lower-bound for the optimal cost function value), improving the solution until the difference between upper and lower bounds reaches a specified tolerance [19]. Tractability is the main computational advantage - instead of attempting to solve one very large problem, lots of smaller problems are each iteratively solved many times. A detailed tutorial on the

Fig.2 – block diagonal constraint matrix structure.

Fig.3 – Master/sub-problem Benders' decomposition scheme.

application of Benders' decomposition in other power system planning problems is given in [20]. Benders' decomposition is often used to separate integer decision variables from linear decision variables in mixed integer programming problems. In the case of the large-scale optimal non-firm wind capacity allocation model designed in this paper, the significant number of time series samples recreating the wind power statistical properties means that decomposition is still required to separate the investment and operational variables, even though they are all linear – it is thus the size, rather than the complexity, of the problem that necessitates a decomposition based approach. The test system of Fig.1 is already adequate and secure at the zero wind integration level, and thus it follows that the Benders' decomposition SCOPF sub-problems are always feasible regardless of the Benders' master problem solution estimate. From (1)-(5), both master and sub-problem stages are obviously still linear programming problems.

V. MODEL INVESTIGATION & SENSITIVITY ANALYSES

The solution of the optimal firm wind capacity allocation problem as outlined in Section IV is investigated for a number of different wind capacity target levels and a wide selection of important model parameter uncertainty sensitivities. In each case, the Benders decomposition restricted master solution initial guess uses an equal allocation of the wind capacity target to each potential wind node – as decomposition algorithm progresses this capacity spread is redistributed in an optimal manner. For un-ambiguous solution comparison purposes, a rather small Benders decomposition upper-bound/lower-bound tolerance stopping criterion of $1 \cdot 10^{-(7)}\%$ is applied in each case, ensuring that each optimization solution approaches the exact optimum point. For consistency, the same conventional plant portfolio is also employed for all wind target levels and sensitivity analyses. Further detail on the sensitivities investigated is outlined in these subsections.

A. Increasing Wind Capacity Targets

The total wind capacity target for Area 1, σ , is varied from 1GW to 7GW in steps of 1GW, corresponding to a maximum wind energy penetration level of approximately 35-40%.

B. Wind Resource Profile Sensitivities

The wind resource profile gradient between the respective wind locations is a key factor in the determination of the optimal non-firm capacity allocation. Lack of suitable historical data length can sometimes be a hindrance for wind integration studies – wind capacity factor is known to exhibit significant variation from one year to the next as illustrated by the historical data in Fig.4, with a number of real Irish wind farms studied over an eight year period (from 2002-2009). Fig.4 illustrates that there is a reasonable degree of dependence between the individual capacity factor variations over the period of interest (2007 was a particularly poor wind year for the system as a whole), yet for some individual years the comparative capacity factor ranking between separate locations is also reversed. For an optimization scheme this would falsely make some locations appear more advantageous for development than others when compared to the long-run average statistical behaviour. An investigation of how a limited wind profile data-set influences the optimal wind capacity allocation is carried out using wind data from the same 10 Irish wind farm locations for the year 2007 alone (sampled at 2-hourly resolution to still give a consistent 4380 samples overall), instead of the 4 year period as outlined in Section III. A comparison of the variation in the test system's 10 wind farm capacity factors from the 4-year base-case data-set to the 1-year sensitivity model is given in Table-I.

C. Load Profile Uncertainty Sensitivities

Generation capacity connection feasibility study requires a reasonably long-term consideration of the system load profile trends. While load peak values, daily load curve shape and spatial demand distribution prediction has always been an approximate process at best (for example Irish customer energy demand dropped unexpectedly by 7% in year 2008 alone due to economic conditions [21]), the impacts of smart-metering efficiency policies and electric transportation development on transmission system load flow and congestion patterns are furthermore greatly uncertain at the present time. Multiple sensitivity analyses for the influence of Area 1 load profile uncertainty on the optimal wind capacity solution were carried out – load profile was either scaled linearly across the entire system, at a small subset of the potential wind plant node locations only, or randomly at each nodal location with uncorrelated samples taken from a uniform distribution of limited range. Specific sensitivity analysis case details are as follows:

- Case C1 – Area 1 load profile linearly scaled across the system to 90% of its original value.
- Case C2 – Area 1 load profile linearly scaled across the system to 95% of its original value.
- Case C3 – Area 1 load profile linearly scaled at bus locations 11, 17 and 33 alone, to 90% of original values.
- Case C4 – Area 1 load profile scaled at each node by random linear coefficients chosen uniformly and independently between 92.5% - 102.5% of original values.

Fig.4 – Irish wind farm inter-yearly capacity factor variation (specific y-axis info not given for commercial sensitivity reasons).

TABLE-I
TEST SYSTEM WIND CAPACITY FACTOR INFORMATION (%)

System Node	3	5	7	9	11	13	15	17	25	33
4-year dataset	27.3	29.6	29.7	29.9	30.3	31.0	31.9	31.4	32.4	33.9
1-year dataset	24.0	28.5	28.7	29.5	28.9	29.9	31.5	28.1	30.2	32.3

- Case C5 – Area 1 load profile scaled at each node by an alternative random linear coefficient set also chosen between 92.5% - 102.5% of original values.

D. Fuel Price Uncertainty Sensitivities

Fuel price volatilities can modify the system's economic dispatch merit-order or locational marginal costs, and thus impact upon congestion management in SCOPF models. Conventional plant fuel price volatility has been observed regularly in the past – long term fuel price trends are thus generally quite uncertain, and assuming fixed deterministic values for their parameters in the non-firm wind capacity allocation problem might be a fallacy. To this end the following fuel price sensitivity analyses were performed on the optimal wind capacity connection model:

- Case D1 – Area 1 and Area 2 gas, oil and distillate fuel prices linearly-scaled to 125% of base case values.
- Case D2 – Area 1 and Area 2 carbon dioxide (CO₂) price scaled to 125% of its base case value of 30 euro/ton.
- Case D3 – Area 1 and Area 2 gas, oil and distillate fuel prices linearly scaled to 75% of base case values.

E. Contingency Management Policy Sensitivity

The optimal non-firm wind capacity allocation formulation of Section IV applies a DC SCOPF model to ensure the test system network thermal power transfer design criteria are not exceeded. The SCOPF concept generally implies an 'N-1' constrained pre-contingency dispatch, enforcing that system security must always be guaranteed in the immediate aftermath of a contingency, even if the probability of such contingencies (for network branches at least) is quite small. Alternative

operational studies [22] have discussed the application of a carefully designed post-contingency re-dispatch policy instead, using advanced communications and control technologies to aid the integration of renewables. While there are still a number of technical challenges associated with such a significant modification of traditional power system operational principles, and while noting that a DC power flow based model will only facilitate a partial investigation of the wider issue, it would be nevertheless informative to estimate the potential for cost reduction and acceleration of wind capacity connections in congested power system areas if such technologies could be demonstrated to function reliably.

A case study analysis investigating the value of such advanced wide area remedial action schemes for the optimal non-firm wind capacity placement problem was thus carried out, with a simple OPF model used to replace SCOPF equations (5a), (5b) in Section IV. Therefore only the relevant intact-network values ($\eta=1$) for α_{ij} are used in (5a), and no generation contingencies at all are included. This simple model therefore implicitly assumes that a feasible re-dispatch is always possible if a contingency ever did occur (though specific constraints might be formulated to ensure this with the methods in [23]), and that the recourse cost of contingencies that do occur has relatively little overall cost-function impacts in (1) as they are relatively improbable.

VI. OPTIMAL NON-FIRM CAPACITY MODEL RESULTS

A. Increasing Wind Capacity Targets

The optimal non-firm wind capacity allocations for increasing Area 1 wind capacity target levels σ are presented in Table-II – clearly the wind capacity factors in Table-I have strong influence on the optimal solution. As the overall target is increased, capacity is first allocated to the high capacity factor nodes, until an economic congestion level is reached – additional wind capacity is then distributed amongst the less advantageous wind resource areas. Wind resource quality is not the only factor of influence however, as evidenced by the optimal capacity allocation to node 9. As this is the location of the three most economical baseload coal generators in Area 1, wind capacity addition to this node would constrain off the system's most cost-effective plant and thus add to the overall energy fuel cost. Table-II also indicates that the optimal non-firm wind capacity solution for each individual location is not always monotonically increasing with increasing overall system target level σ – for example the optimal capacity additions to nodes 15 and 17 fluctuate somewhat.

The cost saving through optimal non-firm wind capacity placement will of course be conditional upon the initial Benders' restricted master problem solution guess at the zero-th iteration. Therefore the full envelope (i.e. the Benders' upper bound progression) of the cost difference between each progressive iteration of the optimal 6GW Benders' algorithm and the final optimal solution cost value is illustrated in Fig.5 – a subset of the corresponding restricted master problem

TABLE-II
OPTIMAL NON-FIRM WIND CAPACITY ALLOCATION, (MW)

System Node	3	5	7	9	11	13	15	17	25	33
σ (GW)										
1	0	0	0	0	0	0	177	70	432	321
2	0	0	0	0	0	0	308	364	704	624
3	0	0	6	0	65	0	914	563	548	903
4	0	228	157	0	175	325	1087	553	523	952
5	0	730	376	0	338	543	1030	415	582	985
6	508	812	637	0	372	651	854	397	717	1051
7	1145	854	639	60	334	683	889	442	812	1140

TABLE-III
6GW WIND CAPACITY ALLOCATION SOLUTION PROGRESSION, (MW)

System Node	3	5	7	9	11	13	15	17	25	33
Iterate										
0	600	600	600	600	600	600	600	600	600	600
1	0	0	0	0	0	0	0	0	0	6000
2	0	0	0	0	0	0	0	0	4406	1594
3	0	3155	0	0	0	0	0	0	950	1895
.....										
20	1899	682	0	0	639	514	168	159	1021	917
21	494	707	1314	101	820	88	536	35	1257	648
22	873	662	177	1078	537	0	638	68	1168	800
.....										
101	478	834	665	0	372	641	834	389	717	1070
102	530	812	661	0	359	659	808	405	704	1061
.....										
154(end)	508	812	637	0	372	651	854	397	717	1051

Fig.5 – Value of optimal non-firm wind capacity allocation, as % of Area 1 total cost, at each progressive Benders' iteration.

solutions at different algorithm iteration stages are also referenced in Table-III. Total combined Area 1 and 2 cost savings in Fig.5 are reported as percentages of the Area 1 cost alone, as this is where the wind capacity allocations are decided – interestingly though, the net cost of Area 1 alone was found to increase from the initial restricted master problem solution guess value at some of the wind target levels.

The corresponding wind energy curtailment percentages are

Fig.6 – Wind energy curtailments for increasing total wind capacity targets.

given in Fig.6. A common trend from Fig.6 is that greater wind energy curtailment generally occurs at the higher wind capacity factor sites, as they will produce more energy when there is no system congestion to compensate for this, thereby reducing the system fuel-cost. While optimal wind capacity placement may have overall power system cost development benefits (through reduced requirement for transmission development etc), the occurrence of wind energy curtailment due to system congestion will have significant commercial implications for wind developers in deregulated power systems however. The resultant economic viability of the different wind farms should therefore be assessed in more detail. A table showing the internal rates of return (IRR) for the wind farm capacity investments in Table-II, corresponding to the wind capacity factors and wind energy curtailment percentages in Table-I and Fig.6 respectively, is given in Table-IV - (for this analysis onshore wind capacity cost was assumed to be 1.05×10^6 euro/MW from [24], expected turbine lifetime was assumed 20 years, annual operational and maintenance costs are taken as 3% of capital cost, turbine availability was assumed 95%, and the renewable energy feed-in support tariff is given as 67 euro/MWh from [25]). Clearly the wind curtailment will reduce the profitability of the investments, and reduction of IRR below a given level (which will vary depending on investor preference and/or the cost of project financing capital) would guide that the investments should not be made.

TABLE-IV
NON-FIRM-CONNECTED WIND CAPACITY INTERNAL RATES OF RETURN, (%)

System Node	3	5	7	9	11	13	15	17	25	33
σ (GW)										
1	-	-	-	-	-	-	12.2	11.9	12.5	13.4
2	-	-	-	-	-	-	12.2	11.9	12.5	13.4
3	-	-	10.8	-	11.2	-	12.2	11.9	12.5	13.4
4	-	10.7	10.8	-	11.2	11.6	12.2	11.9	12.4	13.3
5	-	10.7	10.8	-	11.2	11.5	12.0	11.7	12.3	13.1
6	9.3	10.6	10.8	-	10.8	11.1	11.5	10.8	11.8	12.7
7	9.3	10.1	10.2	10.6	10.1	10.4	10.5	10.1	11.2	12.1

B. Wind Resource Profile Sensitivities

The effect of having an incomplete model of the power system's relative wind resource quality for the optimal 6GW wind capacity placement problem can be seen in Table-V. Using one-year of wind power output data alone for the model of Section IV clearly gives a significantly different estimate of the true optimal capacity allocation solution from that obtained by the four year wind data set. Clearly the more historical data available for study, the more stable is the implicit wind profile model that results, and the more consistent is the optimal wind capacity solution obtained. The sub-optimality implications of the results in Table-V on the overall system operational cost are mild however. Applying the third-row of Table-V as the wind capacity allocation for a SCOPF study using the more representative original 4-year wind dataset lead to a total (i.e. Area 1 + Area 2) increased operational cost of just 0.21% of the Area 1 cost, when compared to that given by the second-row of Table-V when applied to the full 4-year wind dataset.

TABLE-V
EFFECT OF LIMITED WIND PROFILE MODEL-6GW CAPACITY SOLUTION (MW)

System Node	3	5	7	9	11	13	15	17	25	33
4-year dataset	508	812	637	0	372	651	854	397	717	1051
1-year dataset	33	854	565	161	519	593	1182	327	689	1078

C. Load Profile Uncertainty Sensitivities

The results of the optimal non-firm wind capacity allocations with respect to the load profile sensitivity analyses outlined in Section V-C are presented in Table-VI. It is quite interesting to note that aside from some variation in the wind capacities allocated to nodes 3, 7 and 17, the solution deviations are generally quite small with respect to the original model.

TABLE-VI
EFFECT OF LOAD PROFILE UNCERTAINTY-6GW CAPACITY SOLUTION (MW)

System Node	3	5	7	9	11	13	15	17	25	33
Base-Case	508	812	637	0	372	651	854	397	717	1051
Case C1	539	799	585	0	360	632	866	438	715	1065
Case C2	494	808	627	0	366	644	858	424	719	1059
Case C3	538	815	636	0	354	648	861	392	716	1040
Case C4	474	821	650	0	376	656	852	408	705	1059
Case C5	529	813	656	0	367	657	840	394	690	1053

D. Fuel Price Uncertainty Sensitivities

The results of the optimal non-firm wind capacity allocations with respect to the fuel price sensitivity analyses as outlined in Section V-D are presented in Table-VII. The gas/oil/distillate price sensitivities in Cases D1 and D3 are observed to have an intermediate influence on the optimal wind turbine capacity allocations to nodes 3, 13 and 17. The carbon price sensitivity has a somewhat lesser impact. Optimal placement of wind capacity at the best wind resource sites will result in

proportionally more wind energy generation when no network congestion is present, and less wind curtailment when it is – if more wind energy can be produced from a given installed system wind capacity σ , then less conventional plant fuel will be consumed. Therefore the economic benefit of optimal wind capacity placement, as illustrated in Fig.5, will also be somewhat conditional upon conventional plant fuel prices.

TABLE-VII

EFFECT OF FUEL PRICE UNCERTAINTY-6GW CAPACITY SOLUTION (MW)

System Node	3	5	7	9	11	13	15	17	25	33
Base-Case	508	812	637	0	372	651	854	397	717	1051
Case D1	672	825	631	0	338	580	833	348	747	1027
Case D2	417	810	651	0	380	667	878	429	704	1063
Case D3	382	811	638	0	379	701	866	471	676	1076

E. Contingency Management Policy Sensitivity

The results of the optimal non-firm wind capacity allocations with respect to the optimal power flow contingency management sensitivity analysis as outlined in Section V-E are presented in Table-VIII. Operating the power system in post-contingency re-dispatch mode, as opposed to enforcing a preventive security-constrained dispatch strategy, will allow a significant relaxation of transmission network congestion limitations (provided a fast-acting and reliable wide area control mechanism can be implemented). Much more wind turbine capacity can be installed at the better wind capacity factor resource locations, as illustrated in Table-VIII for nodes 15, 17 and 33. The overall operational cost saving is 3.31% of the Area 1 cost.

TABLE-VIII

EFFECT OF CONTINGENCY MANAGEMENT-6GW CAPACITY SOLUTION (MW)

System Node	3	5	7	9	11	13	15	17	25	33
SCOPF Base-Case	508	812	637	0	372	651	854	397	717	1051
OPF Method	0	255	0	0	312	673	1742	828	502	1688

VII. DISCUSSION

Optimization problems related to wind and transmission capacity investments will be unavoidably much larger in scale than previously encountered for conventional generation studies, primarily due to the wider combination of possible power flow situations with many distributed and partially statistically dependent power production sources. The optimal non-firm wind capacity allocation methodology presented in this paper uses historical-recorded multivariate wind power time series data to represent this power flow case diversity. Block-diagonal decomposition separability of the resultant large-scale linear programming constraint matrix is a key simplifying step in the power system modeling strategy employed – whether this is allowable for every network requires careful consideration of operational timeframe wind management issues such as is outlined for the test system of

this paper in [11]. Any attempt to include stochastic mixed-integer unit commitment [26], [27] in the long term wind-transmission planning problem will have massive computational complexity implications however, even if a decomposition scheme could still probably be applied to exploit any constraint matrix structure present. Most large scale optimization problems have regularized structure of some kind – for wind power expansion planning problems of non-standard block constraint layout, more generic block-permutation methods might be applicable [28].

While the Benders decomposition approach does guarantee that the optimal non-firm wind capacity placement problem can be made tractable, this is usually at the expense of computational time requirement - approximately 28 hours on a standard desktop PC for the 6GW wind capacity target in the test system in Section III, for example. From Table-III, this corresponds to $(154\text{-Benders-iterations}) \times (4380\text{-time-series-samples}) = 6,745,200$ individual sub-problem evaluations in total. The benefit of block-diagonal structure is that each of the sub-problems can be solved separately however, and therefore in parallel if such computational capability is available. Most large-scale transmission system operators have a reasonable number of server computers available for repetitive system power flow analysis tasks – the overall computational time for the decomposition approach as presented in this paper could thus be divided by the number of independent processors made available for application to it. Furthermore, a very small duality-gap tolerance was applied in Section V so that precise comparisons of the various sensitivity analysis results could be made. As Table-III and Fig.5 might suggest though, the computational times could be reduced by up to two-thirds in a more practical duality-gap choice (i.e. using 50 Benders' iterations instead of 154) with reasonably mild deviation in the optimal solutions or cost function values expected. A faster software implementation environment than using the MATLAB/GAMS interface would also help.

Further advances in multivariate wind power modeling and optimization problem solution strategies will of course be useful for application of such methodologies in very large scale transmission networks – reducing the number of sub-problems while retaining an effective representation of the statistical parameter inputs is a key possible approach. The wind power profile modeling sensitivity analysis results of Section VI-B are quite interesting in this context – the minor cost function penalty would suggest that reasonably approximate models (i.e. less time series sub-problems) of the wind profiles could give results that are within an acceptable tolerance of solutions achieved from models with very precise fidelity to the true statistical parameters. The results of the load and fuel-price parameter sensitivity analyses of this study are equally informative. In a practical implementation, such parameter uncertainties should be modeled directly within the problem formulation (perhaps by superimposing the wind characteristics to such probability-weighted background uncertainty scenarios) as opposed to using alternative external sensitivities, with the simple effect of multiplying the

constraint matrix sub-problem diagonal length. The surprisingly robust performance of the algorithm results in Sections VI-C and VI-D to model perturbations of reasonably significant magnitude would suggest that fairly coarse representations of these parameter uncertainties may be allowable in wind power transmission models however. Again, beneficial problem dimensionality reduction, and related computational efficiency increases would therefore result. Analysis of the Benders' cuts or indeed the application of master problem 'box' constraints (to prevent too much master problem solution oscillation at the early decomposition iteration stages) could also be useful in speeding the overall problem convergence.

The contingency management policy sensitivity analysis results in Section VI-E are interesting in the context of congested transmission networks and power systems with lengthy transmission access queue delays. While a significant amount of technical work must yet be done to ensure such wide area schemes can reliably be implemented in practice [22], it is useful to know the approximate scale of the economic and policy-advancing value that they can potentially contribute to the wind integration challenge. The implementation costs and/or any reductions in system integrity associated with the inclusion of such technologies can then be framed within the correct economic context.

There is no specific inclusion of power system reliability issues in the analyses of this paper. The same conventional portfolio is maintained throughout to allow comparisons such as given in Table-II, though the higher wind capacity integration cases will of course be slightly more reliable as a result. In a real system, the conventional plant portfolio would be tailored on the basis of the wind capacity credit at that particular wind integration level [13]. Wind capacity geographic spatial spread is known to have an influence on its reliability contribution [29], and should also be considered in the optimal wind capacity allocation solution of a real power system – this is an interesting future research topic.

Non-physically-firm wind capacity connections will generally result in wind curtailment for congestion management reasons, possibly without financial compensation. Although this wind connection strategy clearly has significant system-wide development cost reduction benefits, in a deregulated market the individual wind farms themselves may be exposed to non-negligible financial implications as a result. While the IRR reductions at the various wind farm locations are clearly outlined in Table-IV, these curtailment estimates correspond to a given fixed model of load profiles and fuel prices parameters etc. A detailed analysis of variation in the wind energy curtailment estimates themselves (i.e. curtailment risk) with respect to parameter uncertainties is furthermore highlighted in [30]. Such curtailment risk will be equally important to consider in the investment decision. Given that wind capacity investment constitutes a relatively large up-front capital outlay, particularly with respect to future network parameter uncertainties, the challenge of quantifying and managing such long-term curtailment risk within the market

environment will be a significant enabling factor for cost-effective renewable energy integration – innovative market and/or regulatory mechanisms will likely play a central role in this respect as the wind integration process evolves.

VIII. CONCLUSIONS

This paper outlines in detail the design and study of the optimal non-firm wind capacity allocation problem for a given transmission network. With real historical multivariate wind data sampling used to model wind power variations and spatial inter-dependency, the Benders' decomposition method was applied to exploit the resultant very-large-scale block diagonal constraint matrix structure. Extensive wind profile, load demand profile, fuel price and contingency management sensitivities were examined, and the magnitude of their influence on the optimal wind capacity allocation solution clearly shown. The results of such important sensitivity analyses are useful in the context of formulating more computationally efficient optimal wind capacity connection models. While non-physically-firm wind connections may be advantageous in reducing overall system costs, any reductions in individual wind farm investment profitability should also be carefully accounted for. In congested transmission networks, reasonable economic benefit and timely policy advancement could result from combining new renewable generation projects with advanced communication and control mechanisms for real-time network contingency management, provided such schemes are demonstrated to be sufficiently reliable.

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