Optimal Wind Power Location on Transmission Systems – A Probabilistic Load Flow Approach

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***Abstract*—Renewable electrical energy grid connection is hampered by transmission capacity limitations and public opposition to new transmission development. This paper presents a methodology to find the optimal positions on an existing transmission system network to connect 'firm' wind capacity to reach desired renewable energy penetration targets in a secure, least-cost manner. The methodology accounts for geographical statistical dependencies of individual bus load and wind farm power outputs, as well as the temporal dependencies of the conventional plant unit-commitment process on total system load and wind patterns. This is accomplished using a probabilistic load flow technique based on DC load-flow and recorded load and wind time series. A discretised model of the resultant multi-dimensional probability density function is used to define line flow constraints in a linear programming optimization model. The algorithm objectively allocates wind capacity with respect to the wind resource and transmission capacity in each area.**

***Index Terms*—linear programming, power system planning, power transmission, probabilistic load flow, time series, wind energy.**

I. Introduction

The power systems of many countries all over the world are currently undergoing a rapid increase in the connection of renewable energy. In accordance with efforts to reduce carbon dioxide emissions in the global fight against climate change, [1], and to diversify the generation portfolio for security of supply reasons, many countries have recently pledged to achieve clear future targets in the supply electric energy consumption from renewable energy, [2]. Renewable resource assessments and the relative maturity of generation technology suggest that a significant proportion of these targets will come from wind energy. This aim, coupled with attractive financial incentives, [3], has resulted in a major increase in wind power applications for grid connection agreements.

New generator connection agreements are subject to the power transfer capability of the power system's transmission network. Existing transmission system capacity limitations are compounded by the cost of new transmission line development, the long lead-times to transmission project completion, and the increasingly vocal objections of landowners and residents to transmission planning 'right of way'. In an effort to reach renewable energy targets in a cost-effective and timely manner, there is a clear need to make the optimal use of the existing transmission capacity resource throughout the system, even if this requires the harnessing of wind energy in areas with less attractive wind resources. Previous work has shown the benefit of this concept in wind allocation to distribution systems, [4].

The power system of Ireland is a particularly interesting example of the broader problem. Transmission system capacity is limited in the north-western region with the best wind resources. A recent government commissioned technical report projects that up to 42% of Ireland's electrical energy needs may be harnessed from renewable energy by the year 2020, provided that several technical problems can be overcome, [5]. One of these main barriers is the requirement for extensive transmission system reinforcement. In an attempt to clear up the backlog of wind connection applications in a more efficient manner, the electricity regulator has begun to process applications in groups, resulting in the 'Gate I' and 'Gate II' series of firm connection capacity allocations, [6].

Allocation of a 'firm' connection offer implies secure network operation at all times, under all possible first-case 'N-G-1' contingency scenarios, with no generator curtailment due to network capacity limitations. The traditional transmission system planning methodology applied by many transmission system operators (TSO) to achieve this is primarily based on the method of 'incremental transfer capability' (ITC), subject to the 'N-G-1' security constraint at particularly onerous 'snapshot's throughout the year. These 'deterministic' points are typically the winter day peak (WDP), the summer day peak (SDP), and the summer night valley (SNV), [7]. This has proven to be a generally reliable planning methodology for conventional power generation in the past. A power system network is a distributed infrastructural resource however, and the cumulatively most stressful instance overall may not coincide with the 'worst-case-scenario' for individual transmission lines. This is particularly true in power systems with increased penetration of stochastic energy sources such as wind, and the traditional methodologies of old may not be suitable for the future challenge of wind power grid connection. The behavior of wind power (fluctuating power output levels with a typical capacity factor of 30% in

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Ireland, and the statistical inter-dependence of geographically distinct wind farms) is difficult to integrate accurately to this traditional planning methodology. For these reasons there is a requirement to develop a more advanced methodology for modern power system assessment in the probabilistic domain. The new technique proposed in this paper is related to the established concept of 'probabilistic load flow' (PLF).

The history of probabilistic load flow dates back to the early 1970's. In contrast to traditional power flow, where the bus power injections and line flows are a set of single numbers, PLF uses random variables, (r.v.'s), with specified probability density functions (p.d.f.'s) to describe the statistical behaviour of the power injections and the subsequent probabilistic power flow in each line. In the context of power system planning, the benefit of assessing power flows in the probabilistic domain is that the 'worst-case-scenario' (i.e. the very extremes of the line flow p.d.f.) may be identified in the case of each line, regardless of what time of the year it occurs. This is a powerful advantage in the security assessment of future networks with high wind energy penetration. A number of PLF analytical techniques have been proposed based on the simplistic assumptions of the statistical independence, or linear dependence of nodal power injections, [8], [9], and Gaussian line flow and/or bus power injection probability distributions, [10]. In order to account for the true complex multi-dimensional statistical dependencies between all bus power injection r.v.'s more accurately, 'Monte Carlo' simulation (MCS) techniques based on random sampling appeared from the 1980's onwards, [11], and such principles have been the mainstay of PLF methods since, [12].

As the random sampling MCS is essentially a memory-less process, parameters such as start-up costs, start-up times, ramp rate constraints, minimum up-time and down-time, and energy storage, that are essential to the unit-commitment process applied over 24 hours in a real power system, cannot be modeled. Therefore only simple 'merit-order' dispatch can be applied. To properly account for such temporal constraints, a sequential 'time series' PLF approach has been used in this paper.

The aim of this paper is to find the optimal locations on an intact power system for 'firm' wind farm capacity allocation in a secure and economic manner. No contingency scenarios or transmission system expansion are considered. Section II of this paper describes the optimal allocation methodology in more detail. Section III describes the characteristics of the test system under investigation. Section IV of this paper presents the linear programming optimization stage results, while Section V discusses the wider implications of this methodology in more detail.

II. Optimal Wind power location

A. Geographical Wind 'Smoothing' Assumption

In order to properly define the correct multi-dimensional statistical relationship between the various wind, load and (most importantly) conventional plant time series necessary for a PLF assessment, it is first required to carry out a study of the unit commitment and dispatch process. It is desired to integrate wind energy sufficient to serve a certain percentage of consumer electrical load energy, 'δ_e'. A system wind power time series must be generated to carry out the dispatch process. As the respective capacity allocations to each transmission system bus are not known before the optimization process is complete, some assumptions must be made with regard to the total system-wind behavior. A normalized 1 MW wind farm time series at each of the candidate connection buses is available for study. The required determination of total system wind 'name-plate' capacity to achieve this energy penetration is therefore made difficult by the different statistical parameters and capacity factors of each individual wind site – if transmission capacity allows the selection of the best wind sites, then less overall wind turbine capacity is required.

Each transmission system area has a certain limit to transfer capacity available however, thus it is unlikely that all the wind power capacity will be assigned to one single bus. Therefore the anticipation of a certain spreading of firm capacity throughout the network in the optimal secure solution allows the initial assumption that the total wind power output at any one time will 'smoothen' to an average trend. The average system capacity factor, cf_{avg}, will allow the determination of an average, or 'smoothed', system wind name-plate capacity, C_{avg}, given that the customer yearly energy requirement, E_{load} (in Joules), is known. This averaged nameplate capacity is used to scale the average normalized 1 MW wind series to generate an appropriate representative system wind time series for the unit commitment statistical study. This is explained using (1). When the initial output of the optimization stage is known, the entire unit commitment and optimization process can be repeated with the updated wind locations providing the system total wind power output time series for better accuracy.

$$C_{avg} \cdot cf_{avg} \cdot (60 \times 60 \times 24 \times 365) = \frac{E_{Load}}{100} \cdot \delta_e \qquad (1)$$

B. 'DC' Load Flow

DC load flow is commonly used in transmission system planning as an initial tool to study the 'thermal' or 'active' power capabilities of the network. Other important planning security criteria such as steady-state voltage values, transient voltage stability, short-circuit current ratings etc are typically assessed once the grid is known to be thermally secure, [7]. DC load flow is a linear algorithm, and thus power flows can be solved much more quickly than the full nonlinear AC load flow iterative solution. In the context of optimal wind capacity allocation, the most advantageous feature of DC load flow is the fact that the line power flow solution f_j in each line j is a linear combination of the power injections, P_i, at each bus i, [13], as in (2) below. This allows the DC load flow coefficients, α_{ij}, to be used for constraint definition in a linear programming model. An undesirable trade-off to the fast computational speed and linearity advantages is the problem of inaccuracy, in comparison to the full nonlinear

AC load flow iterative solution.

$$f_j = \sum_i \alpha_{ij} \times P_i \quad (2)$$

C. Multi-dimensional 'Clustering'

Transmission systems that allocate firm network connection permits should be, by definition, secure under all possible normal and first contingency operating scenario conditions. In the time-series PLF approach proposed in this paper, this necessitates the study of power flow in each line, in each of the 8760 hourly sample cases. In a reasonably sized power system, this could lead to an intolerable number of cases required for analysis. During the year, a large proportion of the cases tend to have approximately the same conditions, therefore an efficient algorithm should seek to reduce the study dimensionality by grouping such cases together.

Note that as the optimal wind farm capacities are still as of yet unknown, only the linear impact of the conventional plant and the load at each bus can be calculated using (2) as a 'partial' load flow solution value, f_p, on each line. The net contributory effect of the dispersed wind power on the individual line, as a positive or negative flow, is not yet known. However the multidimensional p.d.f. of the 'partial' line flow solution coincident in time with all of the k normalized 1 MW wind farm time series can now be estimated. Using the 8760 hourly samples in one network scenario (the 'intact' network is the only scenario considered in this paper as no contingencies apply), this continuous p.d.f. can be approximated using a discretisation procedure (akin to a histogram in 'k +1' dimensions (D), with an appropriately chosen 'bin' resolution for each dimension). This effectively groups all of the similar hours together into the relevant 'bin' position. This single 'bin' position 1x(k+1) vector, v, in the (k+1)-D matrix hyperspace can now be used to analytically represent all of the cases which were placed in it. All empty bins are discarded at this stage. In the 'security' environment that is transmission system planning, the frequency of occurrence of cases in each bin is irrelevant, only the fact that the bin has more than zero cases in it. If it occurs only once, it is still worth investigating. In this case the choice of bin 'resolution' is the trade-off between accuracy and the case dimensionality reduction requirement. With a small number of bins, most of the cases will fall into bins that are already occupied, but the bin vector position used to represent all these cases will be a gross approximation to some of its' inhabitant cases. Choice of too high a resolution and no case dimensionality reduction will occur.

D. Linear Programming Optimisation

As no transmission system reinforcement is assumed, and electrical network losses are neglected, the only economic cost to be included in the objective function is the infrastructural cost of the wind farm developments themselves. It is assumed in this paper, that the cost of each development is directly proportional to the capacity of the wind farm. Therefore the system wind development optimization cost function can be related the total installed 'nameplate' wind turbine capacity. The individual wind farm capacities, C_k, are thus the optimization variables. The optimisation cost function is linear and therefore linear programming (LP) optimisation techniques can be used.

The wind energy penetration constraint must also be satisfied from (1). Each wind farm has a different capacity factor. Therefore the total wind energy must equate to that of the 'average' system wind capacity, as described in Section 2a. If the network flow constraints were not included, the unconstrained optimum solution would be to locate all the wind capacity in the wind area with the highest wind capacity factor. However the placement of wind capacity is bound by transmission system capacity constraints. These m constraints, V_{mk}, for each line j are acquired from the 'clustering' process vector positions as described in Section 2c above. The net contributory effect of the dispersed wind power on the individual line can be equated to the k capacity optimization variables scaled by the product of the relevant k DC load flow coefficients and the 1xk bin vector positions of the normalised 1 MW wind discrete p.d.f. It should not cause an overload of line capacity, LC_j, in either the forward or backward direction when added to the relevant 'partial' load flow solution. This optimization model is displayed in (3), (4), and (5) below.

$$Cost = \sum_k C_k \quad (3)$$

$$C_{avg} \cdot cf_{avg} = \sum_k C_k \cdot cf_k \quad (4)$$

$$\sum_j [-LC_j \leq \sum_m [\sum_k \alpha_{kj} \cdot V_{mkj} \cdot C_k + f_{p\,j}] \leq LC_j] \quad (5)$$

A flow-chart of the complete methodology is illustrated in Fig. 1 below.

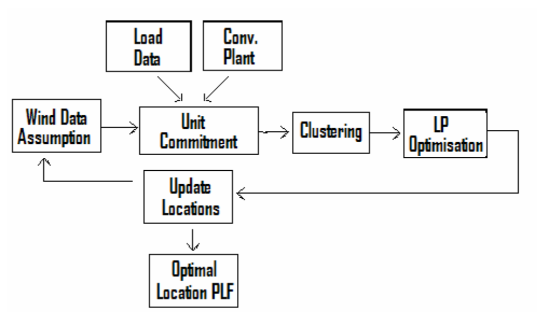

Fig. 1. Flow-chart of the optimal location methodology

III. The Modified 14-Bus Test-System

The test system used for the illustration of this methodology was a modified version of the IEEE 14-bus test system, [14], as depicted in Fig. 2, with a desired wind energy penetration level of 10%. The network topology of [14] was combined with load and wind time series data, and existing conventional plant data, from the Irish power system. Details of the conventional plant characteristics, the maximum load values and the wind farm capacity factors at each bus, as well as the assumed line flow capacity limits, are contained in the Appendix section. The parameters and ratios of the conventional generation plants were chosen in order to be representative of the mixture of 'base-load', 'mid-merit' and 'peaking' plant found on a typical power system. Coal, oil, and peat steam turbines, 'combined-cycle' gas turbines (CCGT), 'open-cycle' gas turbines (OCGT), and 'combined heat and power' (CHP) are the types of plant considered. The total generation capacity was 2022 MW. Possible wind generation connection to buses 2, 3, 5, 9, 12, 13, and 14 was assessed. The recorded year-long load time series (of hourly resolution) were arbitrarily scaled to suit the test system, while preserving the statistical quality of typical load patterns. The peak system load for the test system was 1861 MW. The average load was 1025 MW. The assumed line capacities were chosen based on the zero-wind penetration scenario PLF results. It was assumed, for system inertial and frequency stability reasons, [15], that an arbitrary minimum level of 450 MW of load had to be served by conventional plant at all times. This lead to the occasional curtailment of wind for system security reasons at particularly low load levels, however the low frequency of occurrence of this event was deemed to have a negligible impact on the desired 10% energy penetration level.

The recorded wind time series were normalized to 1 MW capacity to be scaled by the outputs of the subsequent optimal wind allocation process. The recorded wind time series were found to have varying capacity factors. High capacity factor time series are geographically grouped together on buses 9, 12, 13, and 14, in areas of limited assumed transmission capacity. Lower capacity factor wind farms are placed on buses 2, 3, and 5, in the strongly interconnected part of the system. This test system is thus generally representative of the Irish power system wind and transmission resource situation. Though the paper results are based on a small system as an illustrative guide to the power of the algorithm, the methodology applied has been intentionally designed to be applicable to larger, more realistic, power transmission systems.

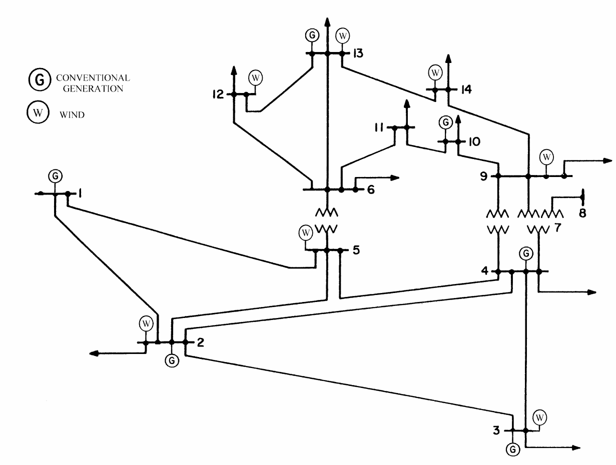

Fig. 2. The modified IEEE 14-bus test system schematic.

IV. Results

A. Probabilistic Transmission Assessment

The year-long hourly time series was applied to the unit commitment software 'Plexos', version 4.903, with the 'mixed-integer programming' (MIP) optimization strategy employed (duality gap tolerance of 1%), to determine the corresponding system dispatch. This dispatch accounted for all of the temporal constraints that are modeled in normal optimal least-cost 24-hour ahead conventional plant commitment.

The comprehensive nature of PLF applied to power system planning in the identification of the 'worst-case-scenario' can be readily illustrated. In fact even in the zero-wind penetration scenario, as illustrated with the line from bus 6 to bus 13 in Fig. 3 below, the time series PLF approach of this paper shows that the worst case power flow in every line of the assumed intact 14-bus test-system did not always occur at either of the WDP or SNV deterministic snapshots. The power flow on this line at these two deterministic 'snap-shot' hours was 136.43 MW and 54.12 MW respectively, while Fig. 3 shows that neither of these hours adequately captured the true highest line loading case of approximately 185 MW.

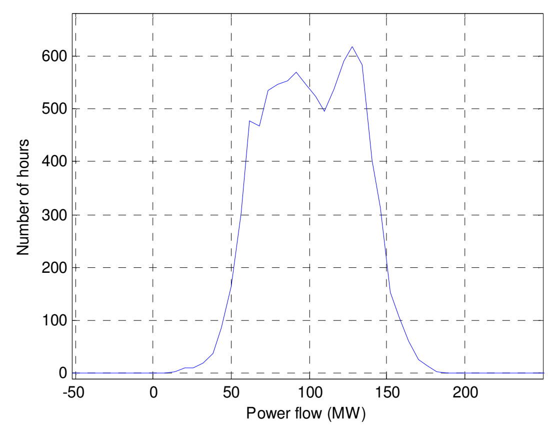

Fig. 3. PLF histogram of line from bus 6 to bus 13, with zero wind energy penetration.

A 'scatter plot' of two conventional plant bus power injections from the probabilistic dispatch in this paper, shown in Fig. 4, illustrates the often complex statistical dependency between conventional generation bus power injections in a real power system. The well defined, yet highly irregularly shaped relationship, illustrates that simple statistical assumptions such as independence and/or linearity of dependence between bus power injections required for analytical PLF methods, in a real power system are incorrect.

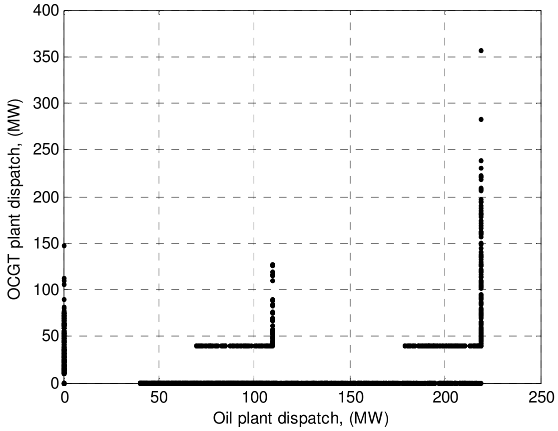

Fig. 4. Scatter plot comparing the dispatch of the oil plant at bus 10 and the OCGT gas plant at bus 3.

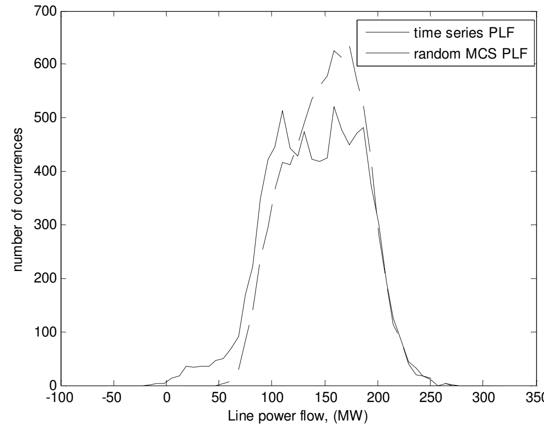

Fig. 5. Comparison of line from bus 9 to bus 10 power flow p.d.f.'s with simple merit-order and unit-commitment model dispatches.

To study the importance of using time series instead of random MCS in preserving the correct temporal behavior of the unit commitment process, a comparison of the type of PLF output that results from both methods was also carried out. A year-long PLF assessment of an equally proportional allocation of the required wind capacity (defined in Section 2a) to each of the 7 wind sites, was obtained in two different approaches. In the first, the time series was applied to the basic merit-order dispatch strategy – this corresponds to a randomly sampled MCS. The second used the time series unit commitment approach, consistent with the true temporal constraints of the conventional plant. As the same net-load time series was employed in both scenarios, no MCS sampling error could affect the results, and thus the only cause for deviation in the two solutions could be attributed to the importance of the temporal unit commitment parameter representation. An example of the deviation in PLF output p.d.f.'s can be observed in Fig. 5 below. As the oil peaking plant at bus 10 is rarely dispatched in the simple-merit order approach, a significant difference in the PLF of the line from bus 9 to bus 10 from the true reality results. This highlights the potential fallacy of random MCS methods that cannot account for hourly sequential dependencies. For this line close to a peaking plant, the error is particularly critical as it occurs at the edge of the distribution, and thus could represent the worst case scenario in some systems.

In a future system with increased wind power penetration, particularly an 'island' system such as the Irish power system, additional flexible plant may be required, [16]. Despite its relative cost compared to base-load plant, such plant may be required online for system security reasons with high wind penetration to cope with unexpected wind forecast error or unusual oscillations in wind output. Thus simple merit-order PLF may deviate even further from reality. In addition, purely random MCS cannot properly model temporally constrained generation resources such as hydro-electric power or pumped-storage either.

B. Optimal Locations

For the multi-dimensional clustering task in this paper, a choice of 10 bins was made for each wind farm, and 25 bins for the partial load flow solution in each line. This required a 25 $x10^7$ multi-dimensional space for each line, populated by 8760 cases. Using the binning technique reduced the number of cases to be studied for each line by approximately 25%. The proportional benefit of this approach would become truly apparent only when 'N-G-1' contingency scenario combinations are all fed into the same space. From initial experience with the modified 14-bus test power system, it was found that the lines from bus 6 to bus 11, and from bus 13 to bus 14 were the transmission 'bottleneck's for wind penetration. Thus in order to reduce the number of constraints even further only these lines were selected for the multi-dimensional clustering process. The optimization software used was the 'simplex' method 'linprog' function in 'MATLAB', [17]. The complete clustering and optimization process required approximately 107 minutes on a 3.6GHz Pentium 'dual-core' driven, 3.5 GB RAM enabled Dell Optiplex GX620 desktop PC. The results are shown in Table I below. As expected, wind capacity was allocated to the high wind capacity sites until transmission capacity in the system 'bottleneck's was exhausted.

Once the complete optimization process was carried out, and the individual wind power capacities determined, the deviation error of the secure optimal system total wind output from the assumed averaged time series input in (1) was analysed. Fig. 6 shows the density function of the error expected from this assumption. This error corresponds to a system power balance deficit or surplus, and could in reality result in un-modeled power flow behavior in the real transmission system. The error was appreciably large in some time instances, as the initial optimal wind allocation is clustered at only three of the seven potential sites. To counteract this problem, the system dispatch and optimization processes were iteratively repeated with the new optimal total wind system time series in order to converge the methodology to the eventual optimal secure solution. The system slack bus balancing requirement from the second iteration is less extreme, as is depicted in Fig. 6.

The process could be repeated if desired for additional iterations to reduce this error even further.

TABLE I
OPTIMAL WIND CAPACITY ALLOCATION (MW)

Iteration Number	Wind Farm Bus Number 2	3	5	9	12	13	14
2	0	125.4	0	0	82.1	107.9	9.92

The second iteration optimal capacity allocations were then fed in to the PLF algorithm, and the yearly power flow was carried out, with all bus net power injection time series now known. The output p.d.f. of power flow in the congested line from bus 6 to bus 11 in Fig. 7 below shows that the line capacity rating of 90 MW was obeyed at all times.

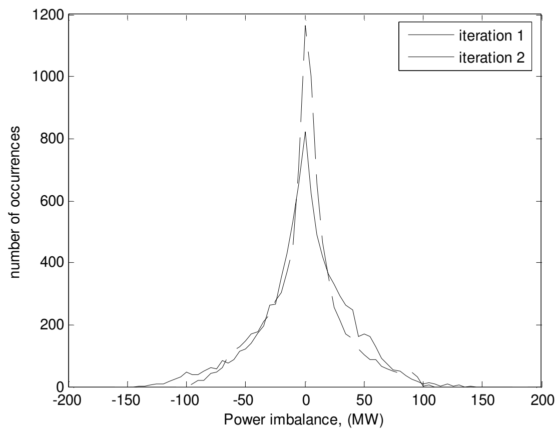

Fig. 6. Histogram of power imbalance of the methodology first and second iteration

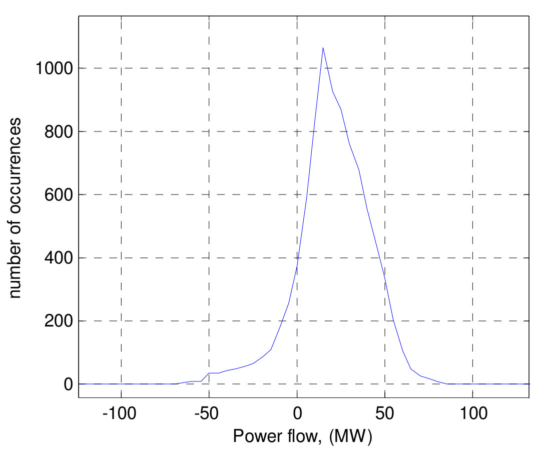

Fig. 7. Optimal wind allocation line from bus 6 to bus 11 PLF result

V. DISCUSSION

This methodology outlined in this paper, while implemented on a small test system, has been devised with a view to application in much larger systems. The importance of the use of sequential PLF has been illustrated in this modified IEEE 14-bus test system. Whether the importance of time-series PLF applies generically to all systems will depend on the generation plant portfolio, the transmission network design, the load and wind patterns and the unit commitment process applied to each individual system. For a large system to study more than 7 wind farms together, while not significantly increasing the optimization constraint dimensionality, each time series as applied here in this methodology could possibly represent a wind 'zone', with many closely dependent wind farms in each zone assumed to share the same statistical behavior. This concept is consistent with the MCS 'stochastic clustering methodology' as introduced by Papaefthymiou *et al* in [12].

The main argument against the use of time series is that often only a limited time length of data has been historically recorded, so it is possible that the available data cannot characterize all possible behavior that could occur in the future. Also, the wind data is sometimes of a sensitive commercial nature, so it can be difficult to access for general system study. In the discretisation and multi-dimensional clustering step of this algorithm as described in Section 2c, it was necessary to assume that the generated discrete p.d.f. from 1 year's data was fully representative of its true continuous form that would be generated by an infinite length time series. This may not be fully representative of the envelope of security risk. However it can be concluded from Section 4b that the error associated with excluding the temporal issues from the unit commitment process would most likely be more critical that the error of a slightly unrepresentative time series, and thus the sequential methodology is to be preferred. Some techniques based on 'auto-regressive moving average' (ARMA) filtering have been published, [18], that generate new time series of arbitrary length from previous data, and may be applicable to this problem. For the time series PLF as outlined in this paper, 7 distinct time series preserving not only the auto-correlative temporal wind characteristics at individual sites, but also the geographical cross-correlative interdependence known to occur in reality, would be required.

This methodology described in this paper is somewhat related to the 'composite' system planning concepts of the traditional vertically integrated utility (VIU), where generation and transmission were planned in tandem. Most modern power systems now operate based on the 'de-regulated' market-oriented paradigm. This does not make the proposed methodology obsolete, however. This paper has illustrated a methodology to find the optimal location of wind power on a transmission system, while respecting normal line-flow security limits, assuming no transmission expansion. In reality, at present the wind connection 'grouping' in the 'pool'-market based Irish system is a preliminary attempt at this. With correct market design, in particular some form of renewable location incentivisation, the benefit of this least cost optimal solution can be achieved in modern power system operation, and thus passed on to the end customer. The disadvantage of renewable connection in areas of less attractive energy resource must be somehow compensated in a transparent manner in the market, so that the system-wide benefits of secure and cost effective transmission system operation accrued by all, are shared fairly by all.

Future work to be carried out subsequent to this paper will integrate the consideration of contingencies and other background generation scenarios to the secure planning methodology of a larger test system. The optimal firm capacity placement algorithm could also be integrated to a transmission expansion planning methodology, a tool likely required to reach higher wind penetration levels.

VI. Conclusion

This paper introduced a methodology to find the optimal locations on a transmission system to connect wind power with respect to the available local wind energy resources and transmission line-flow security limits. The methodology applied a sequential probabilistic approach to cater for the unique characteristics of wind power, with a security assessment based on the adversity of each hourly case and not on the time of year in which they occur. The PLF results also illustrated the importance of correctly modeling the temporal constraints of the unit commitment process.

A small 14-bus test-case network was analysed in this paper, though the methodology can be easily applied to much larger and more complex systems. As expected, the methodology allocated most capacity to regions of high wind capacity factor, with transmission system limitations requiring some wind allocation to poorer wind resource areas.

VII. Appendix

TABLE II
MAXIMUM BUS LOAD VALUES

Bus Number	Maximum Load (MW)
2	100
3	150
4	200
6	400
9	250
10	250
11	100
12	290
13	250
14	100

TABLE III
WIND FARM TIME SERIES CAPACITY FACTORS

Wind Farm Capacity Factor	Wind Farm Bus Number						
	2	3	5	9	12	13	14
	0.24	0.29	0.22	0.25	0.34	0.33	0.31

TABLE IV
CONVENTIONAL PLANT INFORMATION

Bus Number	Plant Description	
	Capacity (MW)	Fuel
1	2*286	Coal
2	1*400	Gas (CCGT)
3	6*90	Gas (OCGT)
4	1* 90, 1*117.6	Peat
10	2*109.5	Oil
13	1*83	CHP

TABLE V
TRANSMISSION LINE ACTIVE POWER CAPACITY LIMITS

From Bus	To Bus	Capacity (MW)
1	2	600
1	5	300
2	3	250
2	4	300
2	5	350
3	4	300
4	5	150
4	7	400
4	9	250
5	6	700
6	11	90
6	12	250
6	13	250
7	8	200
7	9	200
9	10	300
9	14	200
10	11	200
12	13	150
13	14	90

VIII. Acknowledgment

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