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Locational Capacity Credit Evaluation

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***Abstract*—Boosted by U.K. governmental targets of securing 10% of electricity generation from renewable resources by 2010 and 20% by 2020 and widespread public support for renewable energy, distributed generators (DGs) are rapidly increasing in electrical power systems. Among the renewable DGs, wind energy is emerging as the popular choice due to its mature technology and low operation and maintenance costs.**

This paper utilizes the reliability aspects of electrical power systems to provide a probabilistic approach to determine the capacity credit (CC) of distributed generators. Monte Carlo simulations are employed to cater for the stochastic nature of the simulations and each trial is validated using the Newton–Raphson optimal load flow solution. Bernoulli trials are used to simulate the availability of network components. An algorithm to evaluate the capacity credit due to distributed generation (DG) connected in the network is shown. Hence, the amount of conventional generation which can be backed off from the bulk supply point (BSP) of the distribution network can be quantified.

Wind energy production is known to depend on the wind regime experienced by the wind turbines, as well as the geographical landscape and the presence of wind obstacles, which in turn determines capacity credit. Having verified that adding a specific DG at each node does not violate any operating constraints, it was assumed that thermal constraints would not affect CC in this particular system. In a more in-depth study, it is shown in this paper that capacity credit also varies with the different voltage levels at which the wind turbine generators are connected and the loading level of the distribution network. Moreover, it is shown that CC does not vary with the base case reliability, but rather with wind penetration levels.

***Index Terms*—Capacity credit, distribution systems, Monte Carlo simulation, power system planning, wind energy.**

I. Introduction

In the UK, privatization was introduced in the electricity supply industry in England and Wales in 1990 as a way of increasing efficiency and reducing costs. Power system deregulation has opened opportunities for many private energy producers by allowing local generation to meet load demand [1]. Wind power is a potential choice for smaller energy producers due to numerous benefits such as energy efficiency, diversification of energy resources, availability of modular generating plants, ease of finding sites for smaller generators, shorter construction times, lower capital costs, proximity of the generation plant to heavy loads and legal, regulatory and technological drivers for investment in wind energy [2]–[7].

Wind power has seen a steady annual growth above 25% since the last decade [8]. Governments around the world have implemented or are in the process of implementing obligations or incentives to commit to a significant increase in renewable energy penetration. The U.K. has ratified the Kyoto Protocol, pledging for 10% of renewable energy by 2010, which will increase to 20% by 2020 [9].

This paper utilizes a wind power series model to reproduce wind samples for the U.K. The large numbers of potential interactions are simulated with a Monte Carlo reliability model and required indices are evaluated [10], [11]. A distribution network at peak load conditions is used as the test system to demonstrate the process and illustrate the results. It is well established in literature that capacity credit (CC) will depend on the wind regime experienced by the wind generating plants [12], the geographical landscape and the presence of wind obstacles. However, some other factors, such as the base case reliability of the network, the voltage levels at which the wind turbines are connected and their proximity to load centers are investigated.

This paper is organized into the following sections. Section II briefly defines capacity credit and its evaluation in literature and in practice by some companies. Section III describes reliability and how it is measured, and some commonly used reliability indices. Section IV describes in brief the wind model utilized to evaluate wind power in the simulation. Section V describes the Monte Carlo (MC) simulation utilized, and the new technique in evaluating CC. Section VI briefly describes the test system utilized, which is a typical U.K. distribution network. Section VI shows the results of how CC varies in a distribution system and provides a brief discussion for each investigation. Finally, Section VIII states the conclusions.

II. Capacity Credit

CC assigned to a regenerative conversion plant is the fraction of installed capacity by which the conventional power generation capacity can be reduced without affecting the required quality of supply [13]. In broad terms, it can be said to be the amount of conventional resources (mainly thermal) that could be displaced by the renewable production, without making the system less reliable [14]. It is used to avoid ambiguities in comparing different types of generation, particularly when comparing wind to a specific type of generator [15]. CC is particularly useful when calculating wind power plant capacity credit by a reliability index in production-cost or reliability models for strategic system planning [12].

Traditionally, CC was evaluated as a function of wind power penetration for different values of the reliability of the grid as measured by a reliability index [10], [16]. Two loss of load probability (LOLP) methods for evaluating capacity credit are considered: the equivalent firm capacity (EFC) and the effective load carrying capability (ELCC) [10], [15]. If non-firm capacity is added to the grid, EFC is the amount by which firm capacity can be decreased while still maintaining the same LOLP of the grid. ELCC is the amount by which load may be increased in

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presence of additional non-firm capacity while original LOLP of the system is maintained.

Although the majority of capacity credit evaluation studies concentrate on the probabilistic approach to account for the stochastic nature of intermittent generation, it should be noted that other methods have been used. For example, RMATS in the US uses a simplistic rule of thumb of 20% for all sites based on previous studies [17]. Other "rule-of-thumb" models include GE/NYSERDA [18] fixing onshore wind plants capacity credit to be approximately 9% capacity value relative to rated capacity, and offshore wind of approximately 40% from internal studies. PJM [19] assumes a 20% capacity credit for new wind projects. This value is replaced by the wind generator's capacity credit once the turbines are in operation for at least one year, which is then obtained from the chronological energy output of these turbines over the year. The initial values are not flexible though and do not account for the location and individual availabilities, amongst other reasons, of the DG plants. However, simulation probabilistic methods are more accurate and offer more options to power system planners. These probabilistic methods can be subdivided into three main models: numerical probabilistic [16], simulation [20], and analytic probabilistic [21]. While the loss of load (LOL) group gives a good representation of system adequacy, energy indices are required to substantiate the durations of capacity outages and their effect on CC.

In order to evaluate the benefits brought about by the addition of intermittent sources of energy to the grid, it is imperative to be able to quantify the CC of the regenerative generation without jeopardizing the security and quality of supply. In some literature [22], [23], wind turbine speeds are obtained by random draws from a probability distribution with characteristics which do not take into account temporal interactions between load, wind power and conventional generating capacity. However, this paper takes the temporal and spatial correlation of wind speeds over the U.K. into consideration (see Section IV).

III. Reliability

Power system reliability indices can be calculated using two main approaches, namely the analytical and simulation approaches. Traditionally, analytical approaches have been sufficient to provide system planners with the results needed to make objective decisions. However, with ever-increasing interest in a more comprehensive modeling of the system behavior, evaluating a more informative set of system reliability indices is required, and this implies the need to consider MC simulations. Although computationally intensive, MC simulation is capable of modeling the full range of operating conditions [24].

Analytical techniques represent the system by a mathematical model and evaluate the reliability indices from direct numerical solutions [10]. Whilst the indices are obtained in a fairly short computing time, unfortunately, assumptions are frequently required in order to simplify the problem. The resulting analysis can therefore lose some of its significance. Furthermore, the analytical approach based on contingency enumeration cannot model a wide range of operating conditions and is thus subject to several simplifying assumptions [24].

Simulation methods estimate reliability indices by simulating the actual process and random behavior of the system. These methods can theoretically take into account most aspects and contingencies inherent to planning, design and operation of power systems. These include random events such as outage repairs of elements. If the system is simulated over a long period of time, it is possible to obtain a complete picture of the type of deficiencies that the system may suffer and evaluate values of the reliability indices. The first simulation method, known as random simulation simulates a particular time period such as system peak or trough, though not only restricted to these two. Sequential simulation examines each basic interval of time of the simulated period in chronological order.

The choice of a particular simulation approach depends on whether the history of the system plays a role in its behavior. The random approach can be used if the history has no effect, but the sequential approach is needed if past conditions affect present conditions. For example, if the system performance indices at peak time are required, random simulation at a peak time with peak network conditions would be appropriate. In the case of a power system containing hydroplant in which the past use of energy resources affects the ability to generate energy, sequential simulation is required.

In order to deal meaningfully with reliability as a design criterion for distribution, it is necessary to be able to measure it and set goals. Some reliability indices measure only frequency of interruption, others only duration and the rest are composites.

The first group of indices form part of the loss of load, or LOL group [10], [16], [25], [26]. Such indices are capacity or power based. The loss of load expectation or expectancy (LOLE) is the expected period during which the system load exceeds the available generating capacity. The loss of load frequency (LOLF) is the expected number of times that a situation of capacity deficiency (more demand than generation) occurs. The loss of load probability (LOLP) gives the probability that load exceeds the available generating capacity in a given time period. Utilities try to keep this probability as low as possible while maintaining a delicate balance between cost minimization and reliability. The common practice is for system operators to aim for one day in ten years or better, whereby the match between resource and demand is decisive for the said indices [13].

It is more usual to use the "energy index of reliability" (EIR), which is the result of subtracting the EIU from unity. This second category of indices including energy information or the "depth" of the power failure consists of the EIR, energy index of unreliability (EIU), and expected energy not supplied (EENS). The expected unserved energy (EUE) is the expected amount of energy not supplied by the generating system. The EUE is sometimes also called loss of energy expectation (LOEE) or EENS. The EIU gives the ratio of the EUE and the total energy demand [10].

Another method for a utility to measure capacity credit is to maintain a reserve capacity margin that exceeds peak load by a given percentage. Although there is no direct formula for converting between reserve margin and LOLP or EUE, higher reserve margins correspond to a lower LOLP and hence, more reliable system.

In opposition to the previous indices which are the expected or average values of an underlying probability distribution and hence only represent the long-run average values across the whole range of customers, the final group—the customer load point indices group—give a detailed account of individual customers. Common customer point indices include [27] system average interruption frequency index (SAIFI) and customer average interruption frequency index (CAIFI), amongst others.

IV. Wind Model

Wind energy is seen as a crucial player in view of meeting the renewable energy portfolio standard of the British government in 2010 and 2020 [9], [29]. The U.K. being the windiest country in Europe [30] and the fact that wind technology is both reasonably mature and deep into commercial stage [31], [32] suggest that wind energy has a major role to fulfill in electric power systems planning and operation if the targets are to be achieved.

Benefits of wind turbines include low carbon emissions (green energy) [31], modularity, most competitive among all renewable energy technologies and no fuel costs; hence reduced operating costs. Drawbacks of wind generators include a present demand of wind turbines exceeding the supply (leading to a relatively long lead time), problems for planning consent in densely populated areas such as the U.K., as well as the reliability and availability of wind turbines (specially offshore) which imposes high maintenance requirements. Furthermore, by its nature, wind is highly variable and site-specific [32]. Hence, the geographical location is primordial since the power output is highly dependent on the prevailing wind regime. Wind models have to consider factors such as mean wind speed, variance and gusting patterns. Hence, random draws [33], [34] from probabilistic distributions would not give accurate results unless all the above-mentioned factors are considered for a large number of years.

The wind samples used in this study were taken from the output of the multivariate autoregressive moving average (ARMA) model developed by the University of Bath under the EPSRC Supergen initiative [35]. When developing the wind speed model, Met Office stations that offered consistent historical measurement were selected (with the longest possible record to properly capture the variation in wind speeds over different years). The range of wind speed data used began in 1983/84 and goes to at least 1994 and up to the year 2000 in some. The model parameters are estimated and the model outputs are generated using Matlab. A 4th-order ARMA model was used to generate the time-series wind samples which describe both the temporal behavior of the wind speeds and their spatial correlation. Wind speed samples were obtained for 20 representative zones of the U.K., which were further subdivided into four, namely offshore, coastal (within 5 km of coast and elevation under 300 m AMSL), lowland (at greater than 5 km from coast and ground elevation under 300 m AMSL), and upland (at any distance from coast and ground elevation over 300 m AMSL). These were validated for each individual site, as well as the correlation between zones and time of day in relation to wind speed under the project [35].

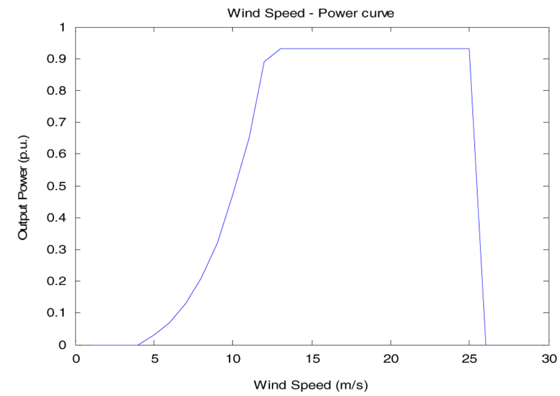

Fig. 1. Wind power curve.

The methodology used the output of the U.K. wind speed model and these values were then scaled to the four different terrain types at each zone and applied to normalized wind power curves to generate normalized wind power time-series. These series were then applied to the installed capacities under study to create the actual output wind power values. In so doing, a typical wind speed-power curve was utilized. This is shown in Fig. 1. This curve was scaled to exclude wake losses (approximated to 8% below rated speed and 0% above), electrical losses within the wind farm (3%) and other miscellaneous losses (1%). Below rated wind speed, the maximum power output is 0.88 p.u. (depending on the wind regime experienced) and wind speeds above the rated value result in a power output of 0.96 p.u. Rated wind and cut-off speeds are 13 m/s and 25 m/s, respectively.

Previous works have modeled wind power as negative load and hence substracted the available wind power from the load [14]–[16], [36]. Treating wind power as a singular deterministic reduction in load reduces the accuracy of system reliability measures with respect to wind resource. However, in this study, wind power obtained from wind turbines connected to the network is modeled as generators providing varying active and reactive power at the specific busbars. An optimal load flow solution is run for each trial, making sure that all constraints are respected.

V. Simulation Modeling

Based on Billinton and Allan's work [11], [16], this work uses reliability indices to benchmark the current network's security and quality of supply as the base case before going on to evaluate the indices for the network with wind penetration. MC simulations are used to represent most contingencies and evaluate the required indices [37]–[43]. Due to the uncertainties in the reserve margin which would vary between distribution network operators (DNOs), it has been decided to use the widely used and traditional LOLP in this work.

For a primary distribution system, each bus may have a load, DG unit(s), reactive shunt device and/or series reactor connected. With each DG, line and transformer having their own reliability index (based on the DG's or circuit's history of outages), their state in the network is randomly deduced by Bernoulli trials using a Mersenne Twister random number generator [44], [45]. Wind turbine generators placed in the system experience a specific windstream (coastal, lowland, upland or offshore) in a specific Bath zone, reflecting their location in the U.K. model. These are fed into the simulation which randomly selects wind samples to keep the temporal and spatial relationship. In the algorithm used, the power exported from each wind farm is obtained from the wind model, after transforming the wind speed by the wind speed-power curve (Fig. 1). Each simulation sees wind turbines experiencing a specific wind regime (Section IV). Since wind farms consist of multiple wind turbines, the farm output is aggregated into a single block of power exported into the network. Also, since wind turbines in a specific wind farm are assumed to be very close together, the same wind speed is experienced by all turbines, with wake losses of 8% below rated speed to cater for the correlation between wind turbines within a specific wind farm. Power output (p.u.) for each individual wind generating plant or aggregated wind farm is obtained by multiplying the p.u. power by the DG rating in the following:

$$P_G = P_R \times R \tag{1}$$

where P_G is the wind plant's output power in MW, P_R is its rated power output, and R is the per unit power obtained from the wind speed-power curve.

After determining the network states, including the availabilities of the circuits and the power output by the DGs, the solution of the power flow equations is performed using the Newton–Raphson iteration. The process of updating the system equations and solving them leads to the evaluation of total DG contribution power, the total system power generation including power from the bulk supply point (BSP), each bus voltage and power imported at buses with DGs connected, each feeder power flow and the total system power losses. The framework is shown in Fig. 2.

Capacity credit results depend heavily on what happens during the utility's peak period. With wind speed greatly varying from hour to hour, capacity credit estimates that are based on a single year of data and modeled without considering this variation would definitely be inaccurate. Some studies have taken into account this variation [46] while others have not [47]. Ignoring this variation could lead to significantly over- or under-estimating the capacity credit [48]. In this work, it was decided to stick with peak load conditions and hence wind samples corresponding to peak time conditions were used.

MC simulations are run for the base case system (without DGs) to obtain the current security and quality of supply. Additionally, the total generation and demand at each trial is recorded. The difference represents the spare capacity, or the amount by which generation exceeds demand (left-hand side of Fig. 3). With DGs in the system, the LOLP is lowered and increases the reliability of the network. Recording the generation and demand, along with the spare capacity gives the right-hand side of Fig. 3.

This is the new improved system reliability. If the base case reliability, and base case LOLP, were to be maintained, the new LOLP would need to increase to the base case LOLP. This, in Fig. 3, represents an additional capacity. In other words, maintaining the same reliability as the base case would actually provide a capacity credit for an installed DG capacity. This method is used to produce the capacity credit to be evaluated each time. Shell sorting is used to sort the spare capacity and the capacity credit associated to an improvement of the LOLP from the benchmark case to the current scenario with DGs is noted.

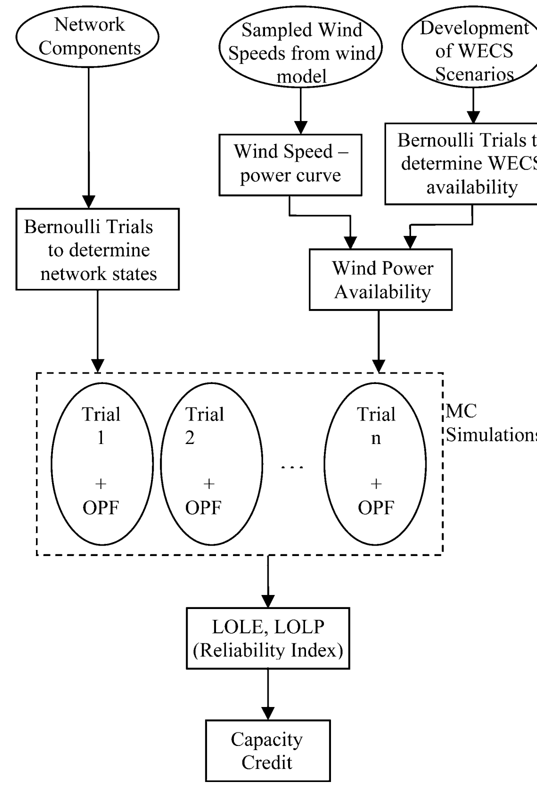

Fig. 2. Modeling framework.

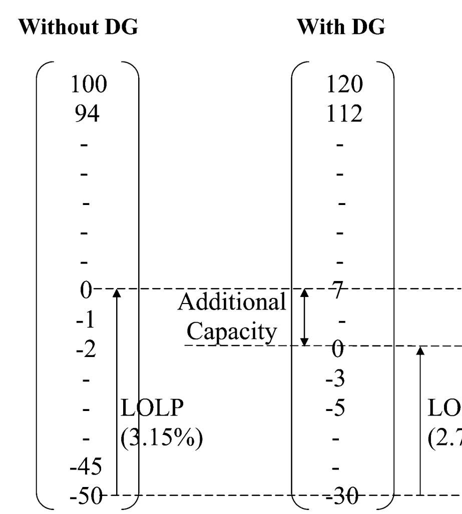

Fig. 3. Capacity credit evaluation.

Wind speed outputs at peak load (winter period—from December to February) were used to evaluate the contribution of DGs at peak load. In the first instance, it was required to verify if DGs can indeed contribute to improving the system reliability. This is verified by adding DGs to the test network and recording

TABLE I
NETWORK LOADS

Bus Number	MW	MVAr
3	5.6	0
5	10.5	0
7	8	0
9	14.1	0
10	9.1	0
13	11.9	0
16	4.1	0
18	3.1	0
20	4.3	0
22	8.6	0
24	3.1	0
26	2.2	0
29	1.9	0
31	9	0
33	4.9	0
48	13.63	3.27
49	13.72	3.44
55	16.45	5.97
57	16.45	5.97
60	1.22	0.46
62	1.22	0.44

the LOLP. Capacity credit measurements were made from specific sites on existing networks and the results verified.

MC simulations are inherently computationally intensive and take a lot of time. Evaluating the capacity credit by connecting one turbine or wind farm one node at a time and running the simulations is effectively a tedious and time consuming process, specially when the network comprises numerous nodes. Consequently, a software was developed to perform the capacity credit calculations at each node automatically. This was tested and validated against the results obtained by individually simulating for each node.

VI. TEST SYSTEM

The system used to validate the methodology was a typical U.K. distribution network. The distribution system is modeled with all its parameters. The bulk supply point, or point of connection to the transmission system, is at 400 kV, and the remaining buses are rated at 132 kV, 33 kV, and 11 kV. These are linked by lines and transformers. The distribution system's demand from the BSP at peak conditions is 135 MVA. With a maximum line utilization of 61.2%, it is checked that there are no thermal constraints for the addition of wind generators to the system at any specific node. Loads in the system are all connected to the 11 kV buses and are shown in Table I below to produce a peak demand of 163 MW, with distributed generators making up the difference. For evaluating capacity credit at peak demand, wind samples used for this paper were the ARMA output between 4 pm to 7 pm for the three winter months in a zone experiencing lowland windstream.

VII. RESULTS AND DISCUSSION

Connecting wind energy to the network depends on the location of wind farms, which is influenced by the wind stream (and variation) experienced at the particular location, the roughness of the landscape, wind obstacles, as well as different properties, such as the park and wake effects (for wind farms) and the hill or tunnel effects [49]. However, when buses are available in the network for connection (without causing any asset thermal violations), it is useful to determine which bus would give a higher

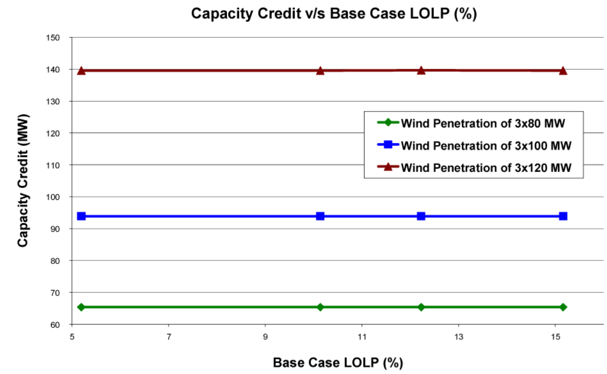

Fig. 4. CC variation with base case LOLP.

capacity credit if the wind farm were to be connected. From an economic perspective, higher capacity credit would imply more energy savings as more conventional power could be curtailed from conventional generation plants.

Three factors affecting the capacity credit were formulated. From literature, CC will vary according to the different reliabilities of the network assets. However, it was thought that CC can be influenced by the base case LOLP, by the voltage levels at which DGs are connected and also the loading level in the network. The first set of experiments varied the base case reliability, but maintained each reliability rate while adding different DG scenarios to the system. For investigating CC at different voltage levels, a similar DG "injection" was applied at each node in the 11-, 33-, and 132-kV buses in the system. The effect of different loading levels was investigated by injecting DGs at each node for different loading levels at some load buses.

1) Capacity Credit Variation With Base Case Reliability: From previous studies of the BSP reliability [39], a BSP reliability index of 0.99 was used. This fact indicates that the BSP is available 99% of a certain time period considered. The algorithm was applied to the test system without any DGs in the first instance (base case), and the base system LOLP was evaluated at 3.08%. From the benchmark LOLP, the reliability of different scenarios with intermittent sources of energy connected to the system can be evaluated and compared. By varying the reliability indices for the BSP and the circuit assets, the same amount and location of DGs were placed in the network, and the capacity credit evaluated. The results are shown in Fig. 4.

Fig. 4 constituted a very interesting set of results in the sense that CC showed no variation with the base case LOLP. In other words, CC only varies with DG penetration, and is unaffected by the base LOLP. This means that varying base reliability rates will vary the LOLP with DGs proportionally, and produce the same spare capacity or CC.

2) Capacity Credit Variation at Different Voltages: An injection of wind energy generation, rated at 10 MW (installed capacity) with variable wind power corresponding to the power output from the wind model, was adjoined, one at a time, to each of the buses in the system, and the equivalent capacity credit recovered from each scenario was recorded in Fig. 5 (grouped by voltage level).

CC varied from point to point between 2.9 to 4.2 MW for a 10-MW injection. With a mean wind speed of 4.2 m/s and wind

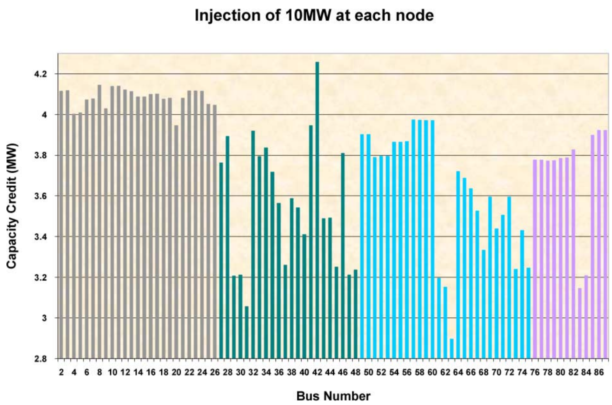

Fig. 5. CC recovered with injection at each node.

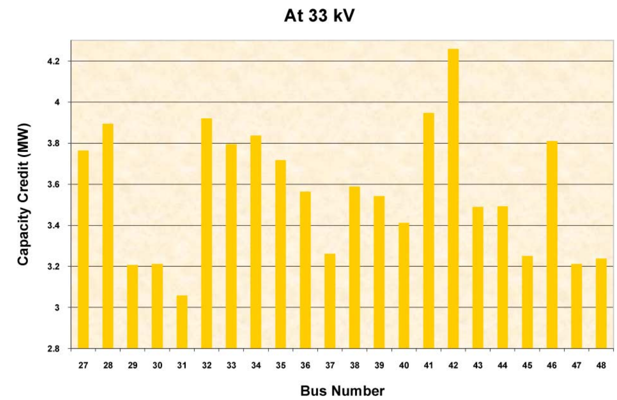

Fig. 7. CC recovered at 33 kV.

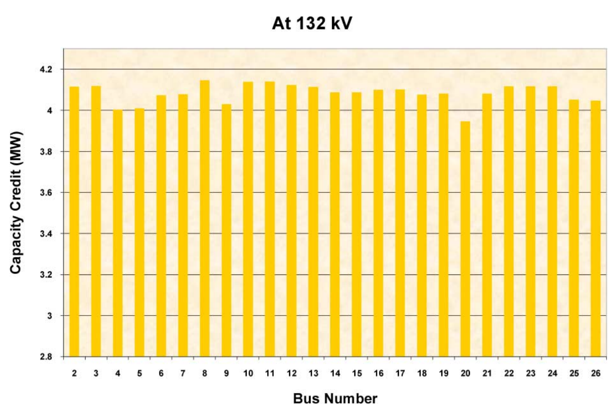

Fig. 6. CC recovered at 132 kV.

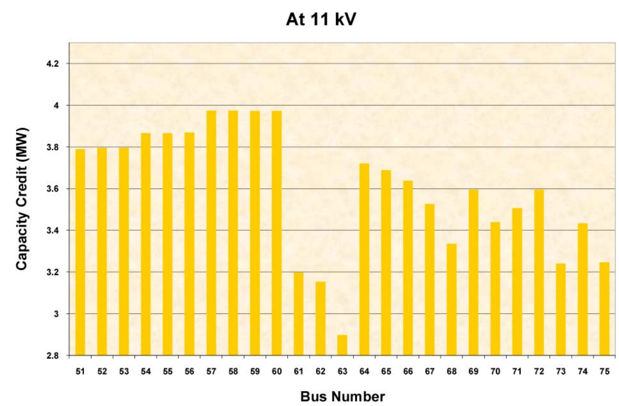

Fig. 8. CC recovered at 11 kV.

speed variance of approximately 2.2, the mean CC for this particular Bath zone and windstream is 3.76 MW with a standard deviation of 0.3265 and variance of 0.1066.

The capacity credit was broken down into the respective voltage levels to see if connecting at certain voltage levels influences capacity credit in any way. Keeping the same axes, but breaking down the capacity credit value into the voltage levels gives Figs. 6–8. Fig. 6 corresponds to 132 kV, Fig. 7 corresponds to 33 kV, and Fig. 8 corresponds to 11 kV. Connecting DGs to high voltage (132 kV) near to the transmission system shows that a higher capacity credit can be recovered if there are no thermal constraints to injecting more turbines in the network. In the 33-kV and 11-kV nodes, CC varies but is generally lower than the 132-kV nodes.

The results suggest that voltage levels can indeed play a role in liberating more CC if there are no thermal or voltage constraints. Hence, DGs should be encouraged to connect to higher voltage levels, as it favours a higher CC. It is to be noted that this is evident by comparing the 132 kV and 33 kV. The 11-kV level is where the substations feeding the loads are connected. In this case, further investigation is required to determine the effect of load on CC.

Distributed generation can be strategically placed in power systems for grid reinforcement, reducing power losses and on-peak operating costs, improving voltage profiles and load factors, deferring or eliminating system upgrades, and improving system integrity, reliability, and efficiency [50]. While these factors are vital for DG placement in the system, DG connection can also be heavily impacted by the capacity credit it liberates, as shown, and that these cost savings should also be considered in optimization processes.

3) Capacity Credit Variation at Different Loading Levels: Finally, the same injection of 10 MW (installed capacity) used for the voltage level investigation is used to see the effects of loading levels. Since all the loads are at 11 kV, it simplifies the task. Looking at the network shows that buses 48 and 49 have nearly the same peak load and are close to each other. A further node, 55 is located further from the load center. These three nodes are all load buses and are used for investigating the loading effects on CC. The CC at each node at peak loading conditions from Fig. 5 is stored. Then, in turn, the loads at nodes 48, 49, and 55 are removed and the automated CC software run for the whole network to determine, each one in turn, the CC value when adding a DG injection at each node. The results are shown in Fig. 9.

It can be seen that CC does vary with different loads connected to the network. By removing the loads at 48 and 49, CC decreased for the whole network. Also, these nodes are quite near to the load center, removing their loads causes a drop in the capacity credit, which means that less power needs to be supplied. Hence the significant drop in CC for both nodes. On the other hand, node 55 is located further from the load centre and although there is an overall drop in CC with the load removal, the reduction is much less than the one noted for nodes

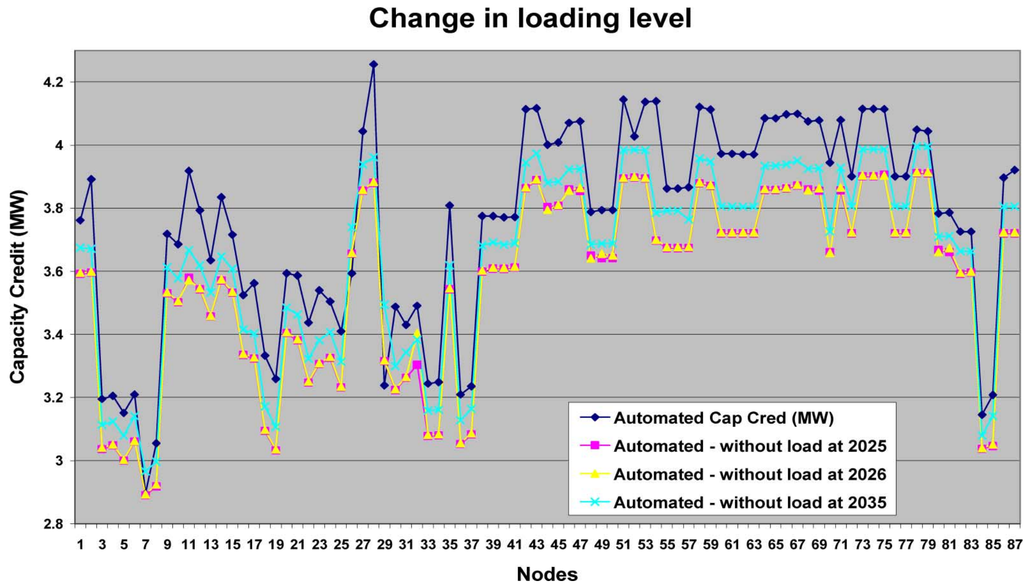

Fig. 9. CC recovered with load variation.

48 or 49. Hence, this confirms that system loading has a distinct influence on the CC recovered from the network. Placing DGs near the load centers could increase CC recovered.

VIII. Conclusion

In this work, it was attempted to use the reliability aspects of a typical distribution system in the UK to determine the capacity credit provided by wind turbines, so as to determine how much conventional power could be backed off from the grid. This was done using a probabilistic approach using Bernoulli trials to determine the network states, coupled with the optimal load flow solution to check for no constraints violation, all within a Monte Carlo framework which can in the first instance determine the quality of supply for the benchmark scenario. After determining the benchmark scenario, the study was extended to systems with wind energy (with a wind model to cater for the high variability of wind, as well as site-specific wind) and the new reliabilities were evaluated. The CC was evaluated.

While it is traditionally known that capacity credit varies with the wind regime experienced by the wind turbines, the geographical landscape and the presence of wind obstacles and the binding limitations of circuit assets ratings, this study focused on the variation of CC with other factors, such as the base case reliability of the network, the voltage levels at which the turbines are connected and system loading of the network were investigated. Because the system is being simulated at peak conditions, with wind samples between 4 pm to 7 pm of the day, wind speeds are higher than the average, which is reflected by higher capacity credit values.

It is concluded that CC does not vary with the base case reliability (or LOLP), but it will definitely vary with different voltage levels at which the DG is connected and amount of loads connected to the system whereby the windfarms are located. In general, higher voltage levels allow for a greater CC, and system loading has a definite impact on CC (more load near the DG in the system account for losses and reduce the amount of conventional power from the BSP). These factors can be used to optimally site DGs in distribution networks, alongside other factors mentioned above.

References

[1] The IET Betta Review 2006, May 23, 2006.
[2] P. A. Daly and J. Morrison, "Understanding the potential benefits of distributed generation on power delivery systems," in *Proc. Rural Electric Power Conf.*, Apr. 29–May 1, 2001, pp. A2/1–A213.
[3] P. Chiradeja and R. Ramakumar, "An approach to quantify the technical benefits of distributed generation," *IEEE Trans. Energy Convers.*, vol. 19, no. 4, pp. 764–773, Dec. 2004.
[4] B. Kuri and F. Li, "Distributed generation planning in the deregulated electricity supply industry," in *Proc. IEEE Power Eng. Soc. General Meeting*, Jun. 6–10, 2004, vol. 2, pp. 2085–2089.
[5] B. Kuri, M. A. Redfern, and F. Li, "Optimisation of rating and positioning of dispersed generation with minimum network disruption," in *Proc. IEEE Power Eng. Soc. General Meeting*, Jun. 6–10, 2004, vol. 2, pp. 2074–2078.
[6] G. R. Pudaruth and F. Li, "Costs and benefits assessment considering deferral of assets expansion in distribution systems," in *Proc. 42nd Int. Universities Power Engineering Conf.*, Sep. 4–6, 2007, pp. 872–878.
[7] N. Jenkins, R. Allan, P. Crossley, D. Kirschen, and G. Strbac, "Embedded generation," IEE Power Series 31, 2000.
[8] R. Karki and J. Patel, "Transmission system adequacy evaluation considering wind power," in *Proc. IEEE Can. Conf. Electrical and Computer Engineering*, May 2005, pp. 490–493.
[9] *Kyoto Protocol to the United Nations Framework Convention on Climate Change,* Jul. 31, 2007. [Online]. Available: http://unfccc.int/resource/docs/convkp/kpeng.html.
[10] M. Milligan and B. Parsons, "A comparison and case study of capacity credit algorithms for intermittent generators," in *Proc. Solar'97*, Washington, DC, Apr. 27–30, 1997.
[11] R. Billinton and X. Tang, "Selected considerations in utilizing Monte Carlo simulation in quantitative reliability evaluation of composite power systems," *J. Elect. Power Syst. Res.*, vol. 69, no. 2–3, pp. 205–211, May 2004.
[12] G. Giebel, "On the benefits of distributed generation of wind energy in Europe," Ph.D. dissertation, Carl von Ossietzky Univ. Oldenburg, Oldenburg, Germany, Sep. 2000.
[13] G. Giebel, "Wind energy has a capacity credit—A catalogue of $50+$ supporting studies," *WindEng eJournal 2004*, May 12, 2007. [Online]. Available: ejournal.windeng.net/3.
[14] R. M. G. Castro and A. F. M. Ferreira, "A comparison between chronological and probabilistic methods to estimate wind power capacity credit," *IEEE Trans. Power Syst.*, vol. 16, no. 4, pp. 904–909, Nov. 2001.

[15] M. Milligan and M. S. Graham, "An enumerated probabilistic simulation technique and case study: Integrating wind power into utility production cost models," in *Proc. IEEE Power Eng. Soc. Summer Meeting*, Jul. 29–Aug. 1, 1996.

[16] R. Billinton and R. Allan, *Reliability Evaluation of Power Systems*, 2nd ed. New York: Plenum, 1984.

[17] I. S. Bae and J. O. Kim, "Reliability evaluation of distributed generation based on operation mode," *IEEE Trans. Power Syst.*, vol. 22, no. 2, pp. 785–790, May 2007.

[18] M. Milligan and K. Porter, "The capacity value of wind in the united states: Methods and implementation," in *Proc. 4th Biennial Conf. University of Queensland*, Mar. 2006, pp. 91–99.

[19] N. Rau and F. Zang, "Dynamic optimizations of Monte Carlo simulation to assess locational capacity, transmission and market parameters," *IEEE Trans. Power Syst.*, vol. 21, no. 1, pp. 36–42, Feb. 2006.

[20] G. E. Consulting, The Effects of Integrating Wind Power on Transmission System Planning, Reliability and Operations. The New York State Energy Research & Development Authority, Mar. 4, 2005, report on phase 2: system performance evaluation.

[21] M. Diesendorf and B. Martin, "Integration of wind power into Australian electricity grids without storage: A computer simulation," *Wind Eng.*, vol. 4, no. 4, pp. 211–226, 1980.

[22] J. O. Kim and C. Singh, "Comparative study of continuous distribution models for power system reliability evaluation," *Proc. Inst. Elect. Eng., Gen., Transm., Distrib.*, vol. 145, no. 5, pp. 566–572, Sep. 1998.

[23] R. Billinton, E. Chan, and G. Wacker, "Probability distribution approach to describe customer costs due to electric supply interruptions," *Proc. Inst. Elect. Eng., Gen., Transm., Distrib.*, vol. 141, no. 6, pp. 594–598, Nov. 1994.

[24] J. Haslett and M. Diesendorf, "On the capacity credit of wind power: A theoretical analysis," *Sol. Energy*, vol. 26, pp. 391–401, 1981.

[25] B. Martin and M. Diesendorf, "Calculating the capacity credit of wind power," in *Proc. 4th Biennial Conf. University of Queensland*, Aug. 1980, pp. 36–42.

[26] A. Chowdhury, S. Agarwal, and D. Koval, "Reliability modelling of distributed generation in conventional distribution systems planning and analysis," *IEEE Trans. Ind. Appl.*, vol. 39, no. 5, pp. 1493–1498, Sep./Oct. 2003.

[27] R. Billinton and R. N. Allan, *Reliability Evaluation of Engineering Systems: Concepts and Techniques*. London, U.K.: Pitman, 1983.

[28] "IEEE trial-use guide for electric power distribution reliability indices," in *Proc. Solar'97*, Washington, DC, Apr. 27–30, 1997.

[29] *DTI, Digest of United Kingdom Energy Statistics 2006,* May 12, 2008, [Online]. Available: http://www.dti.gov.uk/energy/statistics/publications/dukes/page29812.html,

[30] *GB Security and Quality of Supply Standard—SQSS,* May 12, 2008. [Online]. Available: http://www.nationalgrid.com/NR/rdonlyres/FBB211AF-D4AA-45D0-9224-7BB87DE366C1/15460/GB_SQSS_V1.pdf.

[31] R. Ramakumar and P. Chiradeja, "Distributed generation and renewable energy systems[A]," in *Proc. Int. Energy Conversion Engineering Conf. No. 37*, Washington, DC, pp. 716–724.

[32] R. Swisher, C. R. De Azua, and J. Clendenin, "Strong winds on the horizon: Wind power comes of age," *Proc. IEEE*, vol. 89, no. 12, pp. 1757–1764, Dec. 2001.

[33] F. M. A. Ghali, M. M. Adb, E. Aziz, and F. A. Syam, "Simulation and analysis of hybrid systems using probabilistic techniques," in *Proc. Power Conversion Conf.*, Nagaoka, Japan, Aug. 3–6, 1997, vol. 2.

[34] S. H. Karaki, R. B. Chedid, and R. Ramadan, "Probabilistic performance assessment of autonomous solar-wind energy conversion systems," *IEEE Trans. Energy Convers.*, vol. 14, no. 3, pp. 766–772, Sep. 1999.

[35] M. S. Miranda, R. W. Dunn, F. Li, G. Shaddick, and K. R. W. Bell, "Bayesian inferencing for wind resource characterisation," in *Proc. Int. Conf. Probabilistic Methods Applied to Power Systems*, Jun. 11–15, 2006, pp. 1–6.

[36] M. Milligan, "Variance estimates of wind plant capacity credit," in *Proc. Windpower'96*, Denver, CO, Jun. 23–27, 1996.

[37] F. Li, "A fast approach of Monte Carlo simulation for reliability-based risk analysis in distribution systems," in *Proc. IEEE Power Eng. Soc. Transimission and Distribution Conf. 2003*, Sep. 2003, vol. 3, pp. 973–977.

[38] R. Billinton and A. Jonnavithula, "Application of sequential Monte Carlo simulation to evaluation of distributions of composite system indices," *Proc. Inst. Elect. Eng., Gen., Transm., Distrib.*, vol. 144, no. 2, pp. 87–90, Mar. 1997.

[39] O. Bertoldi, L. Salvaderi, and S. Scalcino, "Monte Carlo approach in planning studies: An application to IEEE RTS," *IEEE Trans. Power Syst.*, vol. 3, no. 3, pp. 1146–1154, Aug. 1988.

[40] A. Sankarakrishnan and R. Billinton, "Effective techniques for reliability worth assessment in composite power system networks using Monte Carlo simulation," *IEEE Trans. Power Syst.*, vol. 11, no. 3, pp. 1255–1261, Aug. 1996.

[41] W. El Khattam, Y. G. Hegazy, and M. M. A. Salama, "An integrated distributed generation optimization model for distribution system planning," *IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 1158–1165, May 2005.

[42] R. Billinton and W. Wangdee, "Delivery point reliability indices of a bulk electric system using sequential Monte Carlo simulation," *IEEE Trans. Power Del.*, vol. 21, no. 1, pp. 345–352, Jan. 2006.

[43] N. S. Rau and F. Zeng, "Dynamic optimizations of Monte Carlo simulation to assess locational capacity, transmission, and market parameters," *IEEE Trans. Power Syst.*, vol. 21, no. 1, pp. 34–42, Feb. 2006.

[44] Mersenne Twister, 2008. [Online]. Available: http://www.wikipedia.org.

[45] *Numerical Recipes Example Book (C++)*, 2nd ed. Cambridge, U.K.: Cambridge Univ. Press, 2002.

[46] D. Percival and J. Harper, Value Analysis of Wind Energy Systems to Electric Utilities, Solar Energy Research Institute, Golden, CO, SERI/TP-732-1064, Apr. 27–May 1, 1981.

[47] S. Bernow, B. Biewald, J. Hall, and D. Singh, Modelling Renewable Electric Resources: A Case Study of Wind Tellus Institute, Boston, MA, Tellus No. 91-187.

[48] C. Ensslin, A. Badelin, and Y.-M. Saint-Drenan, "The influence of modelling accuracy on the determination of wind power capacity effects," in *Proc. Eur. Wind Energy Conf. (EWEC)*, Athens, Greece, 2006.

[49] Danish Wind Industry Association, May 12, 2008. [Online]. Available: http://www.windpower.org/.

[50] C. Wang and M. H. Nehrir, "Analytical approaches for optimal placement of distributed generation sources in distribution systems," *IEEE Trans. Power Syst.*, vol. 19, no. 4, pp. 2068–2076, Nov. 2004.

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