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TECHNICAL NOTE

Predicting utility peaks with and without wind generators

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INTRODUCTION

The savings resulting from the addition of wind electric generation to a utility system fall into four categories [1]:

(A) Fuel savings, the dollar value of which depends on the kind of fuel saved and the type of equipment idled (peak or base load, etc.);

(B) Capital investment savings due to a shift from base load equipment to peaking plants during generation expansion;

(C) Capital investment savings due to a reduction in total fuel-burning equipment during generation expansion; and

(D) Operational savings (or, more probably, increased costs) due to changes in spinning reserve requirements, O and M, etc.

Categories (A) and (B) can be assessed either by simulation or from the shift in the load-duration curve due to the additon of wind generation [2]. Category (D) has been addressed by simulation [3]. The subject of this Technical Note is Category (C), which focuses attention on the annual peak load.

UTILITY PEAK LOAD PREDICTIONS

The year-to-year changes in peak demand appear to be composed of a central trend (due to progressive changes in the system and its customers) and random fluctuations (largely due to climatic variations). For the purpose of statistical analysis, we choose to represent the trend of the annual peaks by an exponential, a polynomial, or a logistic–growth curve, and the fluctuations about this trend line by a normal distribution. The implied assumptions present some theoretical difficulties: for one thing, there must be some saturation level in system demand; for another, the annual peak varies in both magnitude and date of occurrence. Nevertheless, in an example we carried out on actual utility data [4], a logistic–growth curve, which is S-shaped, gave good results, and deviations from the assumed statistical behavior were not obvious (Fig. 1).

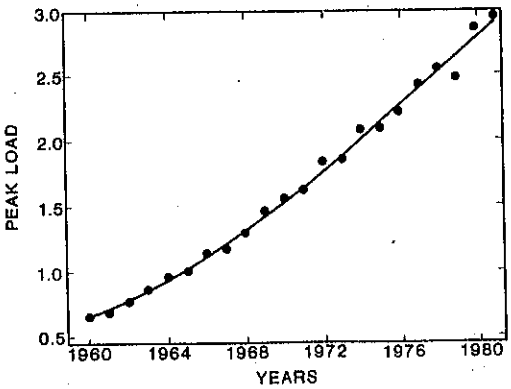

Fig. 1. Example of year-by-year variation of annual peak load on an electric utility system, fitted with a logistic growth curve.

This approach can be used to forecast future annual peaks, using the least-square-fitted growth curve to project the median expected load, and the residual sum of squares to predict the expected statistical deviations from this projected median [5]. This allows us to list the probable peak for some future year at various levels of percentile probability. It should be noted that we need to forecast only a few years ahead, since the impact of the peak load is on peaking-plants, which can be ordered and installed in a comparatively short time.

We propose that the 90-percentile probable annual peak be used as an input into generation expansion decisions. Intuitively, utility planners and executives have done this all along by using the 50-percentile prediction plus an added safety factor.

ALTERNATIVE ENERGY SOURCES

The advantage of the statistical approach becomes evident when intermittent alternative-energy sources are distributed in the system, reducing the load seen by fuel-burning equipment. Since experience with suitable safety factors for these random variations has not had time to develop, some will argue that these generators have no dependable impact on the reduction of future peaks, while others insist that these devices reduce the effective load at the 50-percentile level by an amount equal to their average power output or some other fraction of the rated power of the intermittent sources. Using the statistical approach, we can calculate the change in the 90-percentile prediction for the annual peak when the load is modified by these non-conventional and/or distributed generators.

We have carried out a sample calculation for wind generation in a utility system [4], making the following assumptions:

(a) That the wind-generator power is statistically independent from the system demand. This assumption is supported by the low levels of correlation between wind and load found in a number of studies [6], and the poor correlation between wind strength and daily utility peaks. Neglecting this correlation allows us to combine the probability density of the predicted peak load with the probability density of the wind power by means of a simple convolution integration, in order to obtain the predicted probability density of the load modified by the wind power.

(b) That the wind-generator power curve is similar to that of the large NASA horizontal-axis generators.

(c) That the available wind probability follows the data recorded near Tulsa, Oklahoma.

(d) That the wind generators are located in one general area, and do not benefit from extensive geographical diversity.

On the basis of these assumptions, the reduction in expected peak load due to the additon of wind turbines was calculated for this example (Fig. 2). This shift is shown as a percentage of rated wind-generator power as a function of percentile level, for various levels of wind-generator pene-

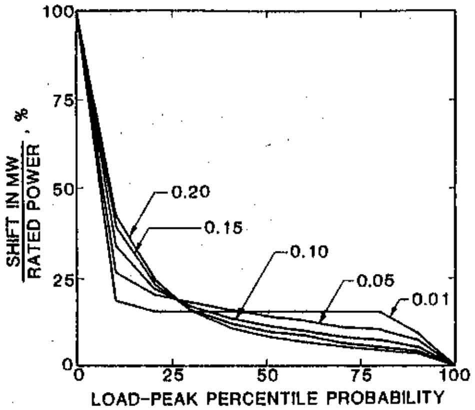

Fig. 2. Net-peak-load reductions (downward peak-power shift expressed in percent of installed wind-generation capacity rating) as a function of their probability of occurrence (expressed as a percentile, where the 90-percentile level might be taken as a reasonable certaintly level), for five levels of wind-generation capacity (1, 5, 10, 15, and 20 per cent of the conventional system's capacity).

tration ranging from 1 to 20 per cent of the system capacity. In interpreting these results, it should be noted that the capacity factor turned out to be slightly less than 25 per cent. Thus, at the 90-percentile level, the "capacity credit" of the wind generator appears to be about 10 per cent of rated generating capacity (or about 40 per cent of average power output) for the small penetration example, and substantially less for larger penetrations.

SUMMARY

While this is only one example, it shows a method for assessing capacity credit under particular circumstances, and indicates that a realistic assessment falls somewhere between the extreme positions taken in the past. We have also demonstrated the negative effect of increasing penetrations.

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