SIMPLIFIED PERFORMANCE MODEL FOR HYBRID WIND DIESEL SYSTEMS

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ABSTRACT

This paper describes the latest preliminary performance (or screening) model developed for hybrid wind/diesel systems at the University of Massachusetts. The corresponding computer code (Wndscreen3) allows one to rapidly evaluate the performance of wind/diesel systems with one or more identical multiple wind turbines, one or more identical diesels, with or without energy storage. In addition to an overview of this model, the paper presents two examples of its use, including a comparison of performance results with Hybrid2, a detailed model for hybrid system performance modeling.

KEYWORDS

Wind, Hybrid Power Systems, Wind/Diesel, Diesel, Wind/Diesel Performance Model

INTRODUCTION/ BACKGROUND

At the present time, the designer of hybrid wind energy systems has the choice of a number of performance simulation models for such systems. The majority of these models and their resulting computational codes, however, are quite detailed, require a large number of input variables, and take some time to obtain the desired performance prediction results. Thus, there is a need for simplified models/computational codes that can be used to obtain preliminary (or screening level) system performance results. The objective of this paper is to present such a model, developed for the preliminary performance prediction of simple wind diesel hybrid systems. The modeled hybrid system consists of one or more identical multiple wind turbines, one or more identical diesels, and may contain energy storage. The analytical basis of the model is based on a combination of previous University of Massachusetts hybrid systems model developed for no storage and storage hybrid wind diesel systems. The no storage case is based on the use of statistical methods. For the case of storage systems (which assume an ideal storage, i.e., no losses), synthetic load and wind data may be generated using a Markov process method. For load generation and wind speed modeling, this method results in a time series with a specified mean, standard deviation, autocorrelation and specified lag, and probability density function. Also, a diurnal sinusoidal variation, starting at a specific hour, may also be imposed.

The paper also demonstrates the use of the resulting computational code (which is readily available on the Internet) that requires a small number of input variables, is user friendly, and features a graphical interface. This code can also be used to model an autonomous wind/ battery system. In addition to a description of the model and resulting code, the paper gives the results of sample calculations for a number of representative hybrid wind diesel systems and a comparison of these results using Hybrid2, a detailed model for hybrid system performance modeling.

ANALYTICAL MODEL SUMMARY

This analytical model of a wind/diesel system, following the example of an earlier screening model (Manwell and McGowan, 1995), is designed to be applied over periods of time when the wind resource and load are uncorrelated. In practice, this is the case for seasonal or monthly case studies. Thus, a complete year can be comprised of a number of model runs. The following summary presents an overview of the basic subcomponent model assumptions, input requirements (preliminary estimates or guesses can be used) and the system control/ operating strategy used for the latest version of the screening model.

Subcomponent Models

Wind resource.

The subcomponent model for the wind input consists of a long term average wind speed, standard deviation, and autocorrelation. These would correspond to averages taken over intervals of one hour (if data had been collected). A Weibull or Rayleigh probability distribution is assumed to represent the wind resource.

Wind turbine power.

Wind power from a single machine is calculated from the wind speed distribution by using a wind turbine power (W) vs. wind speed (V) curve. Multiple wind turbines are also allowed, but they are assumed to be identical. They can either be uncorrelated or correlated.

Diesel power.

The diesel generator(s), which are assumed to be identical, are modeled by a conventional linear fuel (F) vs. power (D) curve of the form: $F = a + bD$.

Load.

The load is characterized by the average and standard deviation of the real power required by the consumers over the time period. As with the wind, the load values would correspond to averages taken over one hour. The load may be assumed to follow a shifted Rayleigh distribution (i.e., minimum >0).

Dump load.

A dump load is assumed to exist such that all power produced in excess of the system's requirements can be dissipated. This could occur either due to excess power production from the wind turbine(s) or as a result of the minimum allowed power of the diesel(s).

Storage.

The overall model provides for a choice of three storage options:

1) No Storage,
2) Power Smoothing Storage, and
3) Long Term Storage.

For power smoothing storage, it is assumed that rapid power fluctuations due to turbulence or short term load variability can be ignored. In this idealized case, the wind power input approximately equals the load. For the case of long term storage, an ideal storage system is assumed. That is, losses into and out of storage are not considered, and there is no restriction on the rate at which energy can be taken from or placed in storage. In this option, the storage is characterized by its maximum energy capacity (in kWh).

System Control or Operating Strategy

The basis of the wind/diesel system model is the application of an overall energy balance equation. In its most basic form the energy balance is expressed by:

$$D = L - W + DP - U$$

where: D = Power delivered from the diesel generator(s),
L = Power required by the load,
W = Power delivered from the wind turbine(s),
DP = Power dissipated in the dump load, and
U = Unmet load.

As described below, the overall model uses different analytical techniques for the various system storage options. More detail will be given for the long term storage option (especially the method of data synthesis) since it represents our newest addition to the overall screening model.

No Load and Power Smoothing Options.
For the no load and power smoothing options, the screening model is based on the purely statistical methods used in a previous model (Manwell and McGowan, 1995). That is, when the wind speed is not correlated with the load, it can be shown (see Hunter and Elliot, 1994) that the average fuel usage of the diesel(s) is given by:

$$F = \int_{L=0}^{L=\infty} \int_{0}^{W_{max}} F(L-W)\, p_W(W)\, p_L(L)\, dW\, dL$$

where: F( ) = Diesel fuel consumption as a function of net diesel load, L-W;
L = Total system electrical load;
$p_W(W)$ = Probability density function of WTG power;
$p_L(L)$ = Probability density function of system load;
W = WTG power; and
W_{max} = Maximum possible wind power.

For computational purposes, the double integral above is approximated by methods summarized in Manwell and McGowan (1995)

Long Term Storage Option.
The long term storage option is based on time series analysis method, and a simple control (or dispatch strategy). The time series data is assumed to be hourly. Real data can be used or, as discussed below, it can be synthesized by a built in synthesizer program. The major steps of the control strategy are:

1) Any wind energy that is available is used to reduce the load. This results in a net load.
2) Storage is checked to see how much, if any, energy may be taken to further reduce the net load.
   i) If possible, the entire net load is supplied by storage. In this case, the diesels are not used at all.
   ii) If some, but not all of the net load can be supplied from the storage, then that is done. The remainder of the load is supplied by the diesels, if possible.
   iii) If the net load is negative, i.e. if there is extra energy available from the wind, then that energy is put into storage, up to the capacity of the storage.

3) The number of diesels that are running in any time step is determined by the average net load during that time step. When there are multiple diesels running in the system, all but one of them runs at rated power. The remaining diesel follows the load.

Data Synthesis for Long Term Storage

In theory, it is possible to develop a long term wind/diesel system model which is purely statistical in nature. For example, University of Massachusetts researchers (Manwell, Deng, and McGowan, 1994) describe one such model, but it only applies to a single diesel and single wind turbine. It is also based, on the assumption of a linear wind turbine power curve, and the capacity of the storage system is limited. It has, so far, proved to be more straightforward to use a time series approach, and use statistical methods to synthesize the time series data. In the method used in the latest model, data is synthesized which has a number of desired summary characteristics. These are the mean, the standard deviation, the type of probability density function, and autocorrelation at a specified lag. In addition, a diurnal cycle may be superimposed

The data synthesis method used here employs a Markov process approach. It is an adaptation of one proposed by McNerney and Richardson (1992) and then further developed by Manwell, et al (1994). For wind speed, the method produces a time series with a specified mean, standard deviation, probability density function (Rayleigh or Weibull), and autocorrelation. A diurnal sinusoidal variation, starting at a specified hour, may also be imposed. The load generator is similar to that for wind in that it results in a time series with a specified mean, standard deviation, probability density function and autocorrelation. In this case, however, a shifted Rayleigh is used for the shape of the target probability density function. A diurnal sinusoidal variation, starting at a specified hour, may also be imposed. The complete process for synthesizing data is illustrated in Figure 1.

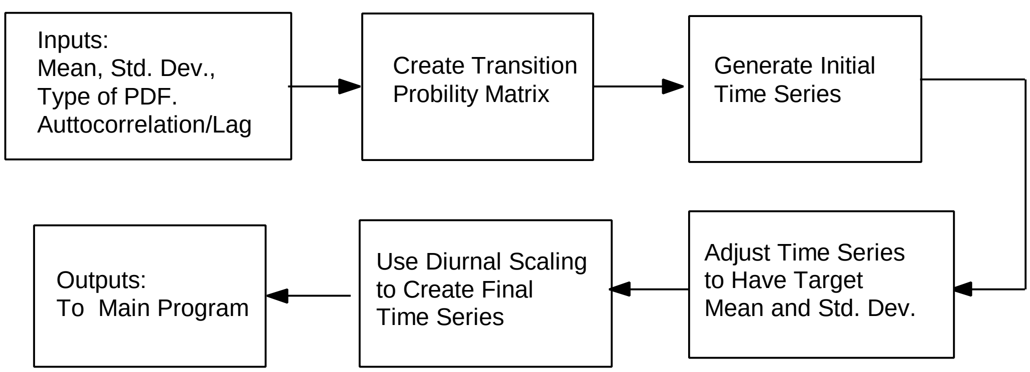

Fig. 1. Flow Chart of Data Synthesis Process

As can be seen, there are five key steps:

1) Inputting the “target” parameters,
2) Creating a Markov process transition probability matrix,
3) Generating an initial time series using the process transition probability matrix,
4) Adjusting the time series if necessary to ensure that it has the desired mean and standard deviation, and
5) Multiplying the time series by a diurnally varying scale factor.

A short summary of these steps follows:

Data Inputs.

For the data synthesizer used in this model, the inputs are defined as the “target “ (mean, standard deviation, type of probability density function, and autocorrelation at a specified lag). These values will then determine the characteristics of the probability density function and accordingly the probability density vector, which is described next.

Markov Process Transition Probability Matrix.

The method of generating a time series from a Markov process transition probability matrix (TPM) is documented in a recent technical report (Manwell, 2000), so it will only be described here briefly. The method initially assumes that any time series can be represented by a sequence of "states." The number of states is chosen so that not only generated time series do not appear too discontinuous, but also that calculations are not too burdensome. The Markov TPM is a square matrix, whose dimension is equal to the number of states into which a time series is to be divided. The value in any given location is the probability that the next point in the time series will fall (i.e. will make a transition) into the j^{th} state, given that the present point is in the i^{th} state. An additional consideration is that there must be a known relation between the state number and the value of that state. This value is normally the midpoint of the state.

The most intuitive way, and most common way, to generate a Markov TPM is to start with a time series of data. Generating a TPM without using an initial time series is considerably less intuitive. Nonetheless, it is possible to do so in such a way that the probability density function of data generated with its use will be equal (given a sufficient number of points) to a target probability density function. The method used for generating a TPM without use of time series data is discussed in more detail in another report (Manwell, 2000). Since there is a direct relation to the pdf and means and standard deviations, those values will be preserved as well. This part of the process (above) results in a TPM, which can generate a time series with values close to the target values. (They will not be exactly the same, as discussed below.) The time series will have an exponentially decreasing autocorrelation, but will not necessarily be equal to that of the target.

Generation of Time Series Using Transition Probability Matrix.

A time series is generated by first assuming a starting value. This can be any number corresponding to a real state. A random number generator is then used to select the next point, based on weightings which are proportional to the probabilities in the row determined by the present state.

Adjusting Time Series to Correct Mean and Standard Deviation.

As noted above the mean and standard deviation of the synthetic time series will not necessarily be exactly the same as the target values. This is because the time series includes a finite number of points, determined by a random number generator as well as the TPM. As the number of points increases the summary characteristics of the time series should approach the target values, but that is not a helpful solution in most cases. Since the most significant parameter is the mean, and the next most significant is the standard deviation, the approach taken here is to scale the time series so that the mean and standard deviation is equal to the target. This is done by first finding the mean and standard deviation of the time series. The calculated mean is subtracted it from each value of the time series to obtain a new time series of zero mean. The zero mean data is then multiplied by the ratio of target standard deviation and the calculated standard deviation, giving a second new series, but with the desired standard deviation. To this time series is added the desired mean. The resulting time series will then have both the desired mean and standard deviation. No attempt is made to correct the probability density function.

Diurnal Scaling of Time Series.

It is sometimes desired to include diurnal fluctuations in synthesized data. The data may be diurnally scaled by multiplying each point by a sinusoidal scale factor. The period of the sinusoid is one day. The user may select the time of day of the maximum, as well as the ratio between the maximum value and the mean. Note that this method will preserve the mean, but may somewhat distort the standard deviation and the probability density function.

COMPUTER CODE

The screening model (Wndscreen3) has been coded in Microsoft Visual Basic 3.0 and is available on the Internet at http://www.ecs.umass.edu/mie/labs/rerl/Software/Index.html. The wind turbine inputs include the wind turbine power curve and the number of wind turbines. The power curve may be read in from a file or input on the screen. If there is more than one wind turbine, the user may select whether or not (default assumption) all the wind turbines are correlated. The diesel inputs include the full load rated power, the minimum allowed power, the full load fuel consumption, the no load fuel consumption, and the number of (identical) diesels. The load input for the no storage and power smoothing cases, as described previously, may be a separate time series or may be produced by the data synthesizer.

The wind input for the no storage and power smoothing cases consist of the long term mean wind speed and standard deviation of the wind speed, and the short term variability (turbulence intensity). For the long term storage case, the input consists of a time series. This time series may be a separate file or it may be produced by the data synthesizer. The storage input is simply the total amount of energy, in kWh. The outputs from WndScreen3 include the average available wind power, the average diesel power, the average fuel use, the average dump power and the average unmet load.

EXAMPLE OF USE OF COMPUTER MODEL

In order to illustrate the operation of WndScreen3, a number of runs were made for a case study on an island in Boston (MA) Harbor. A commercially available wind turbine modeled was rated at 60 kW. The number of turbines was one, three or five. For these cases, a system using one diesel, rated at 110 kW, was examined. A typical linear power curve was assumed, for which the no load fuel consumption was assumed to be 20% of the full load fuel use. Three types of cases were considered: no storage, power smoothing, and long term storage. In the latter case, storage values of 10, 100, and 1000 kWh were used. Summary characteristics of data collected in 1998 and 1999 were used as inputs. Based on this data, the mean wind speed was taken to be 5.77 m/s and its standard deviation was 3.09 m/s. The mean load was 36.6 kW with a standard deviation of 10.78 kW. Variability of the wind and load were taken to be equal to WndScreen3's default values (0.12 and 0.05 respectively.) The autocorrelation of both wind speed and load were assumed to be 0.92 at a lag of 1.

To illustrate the results in a general way, they are presented as ratios in Figure 2. Specifically, the fraction of useful wind power is plotted against the ratio of the available wind power to the average load. For comparison purposes a line for the ideal case is also included. The figure illustrates some well known observations. When the wind power is small compared to the load most of the available power can be used, and storage has little value. As the ratio of average wind power to load increases, storage has a progressively greater effect. In these runs increasing the number of turbines increased the wind power. Note that this example case assumes that the turbines are uncorrelated, which results in a considerable smoothing effect of short term power fluctuations. Accordingly, there is little benefit to be seen in using short term storage. It should be noted, however, that the implications would be considerably different if the same wind power to load ratio were obtained by decreasing the load.

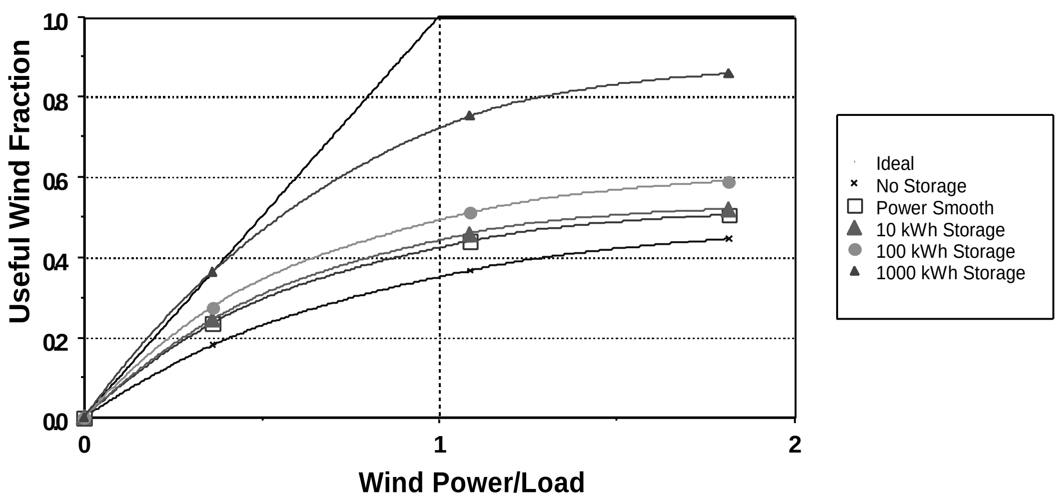

Fig. 2. Performance Predictions from WndScreen3

COMPARISON OF SCREENING MODEL WITH DETAILED MODEL

WndScreen3 is, as previously indicated, a screening level model, and it is not intended to be as accurate or as versatile as are more detailed models such as Hybrid2 (Manwell, et al., 1997). Nonetheless, it is instructive to compare the two models, so as to gain some idea as to how close the two models may be. In the following example, Hybrid2 was run with the original data from which the summary data used in the previous example was derived. This data consisted of the 1 year of hourly data on which the summary data used in the previous example was based. Hybrid2 was run using three operating strategies:

1) no storage,
2) power smoothing, and
3) long term storage.

The dispatch strategy was set to be as close as possible to that used in WndScreen3. Specifically, the load is supplied preferentially by the wind and the storage. Storage was made ideal, and losses were ignored. The diesel was allowed to operate only to make up any deficit in supply from the wind turbine or the storage. For comparison in the long term storage cases, WndScreen3 was run with the real data as well as the synthetic data.

The results of the comparison runs for the no storage and 1000 kWh storage cases are shown in Figure 3. As can be seen, for the no storage cases, the results are nearly indistinguishable. For the long term storage case, Hybrid2 and WndScreen3 are also nearly indistinguishable when real data is used in both models. When the synthetic data is used in WndScreen3, that model overestimates the fuel saving somewhat, particularly when a single wind turbine is used. In this case the difference is about 10%. The difference appears to arise because of the seasonal differences between the wind and the load. These are not accounted for in the data synthesis algorithms. It should be noted, however, that when seasonal summary data is available WndScreen3 could be run multiple times to improve the results. When there is more wind power available the results are closer, presumably because there is a greater number of occasions when there is excess energy to supply the storage.

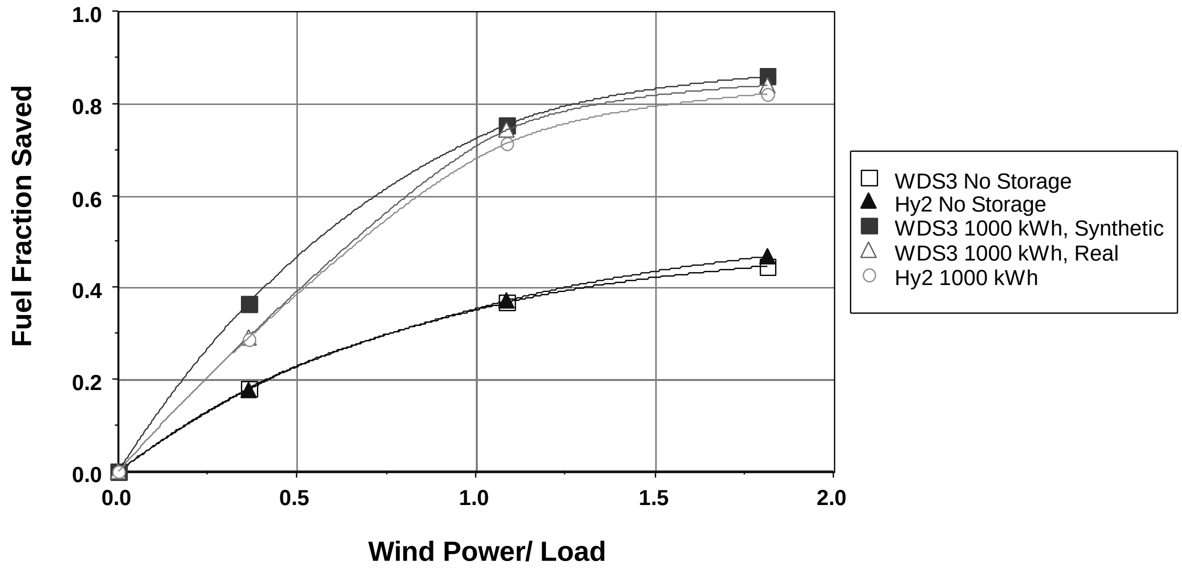

Fig 3. Comparison of WndScreen3 and Hybrid 2

CONCLUSIONS

The results of the examples and the comparison with Hybrid2 illustrates that WndScreen3 can yield predictions close to those of a much more detailed model for a number of cases of interest. Thus, this model can be quite useful in giving a preliminary assessment of the potential for a few types of wind/diesel systems in an arbitrary application. This is not to say, however, that it can supplant a more detailed analysis when making final decisions. The results of WndScreen3 are often optimistic when compared with more detailed models, in particular since the storage model is so idealized. On the other hand, there are certain dispatch strategies, which can make more effective use of the storage and the diesels than can the simple one used in WndScreen3. What WndScreen3 can do, however, is to quickly indicate when a more detailed analysis is warranted.

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