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Reliability Indices Assessment of a Small Autonomous Hybrid Power System Using Aggregate Markov Model

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Abstract: **Distributed Energy Resources such as Wind, Solar, Tidal, Biomass, Geothermal and Hydropower constitute a type of power generation and received much attention as alternatives for conventional power generation. Distributed Energy Resources (DER) will help to reduce the green house gases emission. In this project, focus is made on reliability assessment of Small Autonomous Hybrid Power System (SAHPS). SAHPS consists of 10-kW Wind Turbine Generator (WTG), 5-kW Solar Photo-Voltaic (PV) unit and 5-kW Pico-Hydro unit. Data Synthesizer software will be used to determine the hourly wind speed, hourly solar irradiation, hourly water discharge and hourly load data from the monthly data of 1 year. Markov models for the WTG, PV, Pico-Hydro and System Load with transitions among all states will be established. Aggregate Markov model is developed from the Markov models of distributed resources with transitions among all states. In this project, reliability indices like Loss of Load Probability (LOLP), Loss of Load Frequency (LOLF), Loss of Load Expected (LOLE), Loss of Load Duration (LOLD), Expected Energy Not Supplied (EENS) and Energy Index of Reliability (EIR) will be evaluated for Aggregate Markov model.**

All the above analysis will be carried out in MATLAB software environment. Results for Aggregate Markov method will be presented and analyzed.

Keywords: **Distributed Energy Resources,Solar Photo-Voltaic (PV) unit, reliability indices, Markov method**

1. INTRODUCTION

Distributed energy resources have been considered as the important source of power generation, because of free availability of natural resources. In general, uses of hybrid power system will reduce the total cost. Wind and solar generation units are the mostly used energy resources for supplying load in hilly and rural areas. In addition to these resources, other sources like Pico-Hydro, tidal, geothermal, biomass etc. can also be used to meet the variation in load demand.a small Autonomous Hybrid power system (SAHPS) is a system that generates power in order to meet the low power demand. Distributed energy resources (DER) are used as a major source of energy in SAHPS and they are usually located in remote and sparse areas.Renewable energies, such as solar, wind, geothermal, biomass, tidal, and hydropower, constitute a type of distributed electricity resource and have recently received much attention as alternatives for electricity generation. The use of renewable energies can mitigate the greenhouse effects to meet the strict requirements. In particular, wind and solar Photovoltaic (PV) power generations play essential roles in a grid, especially in a small isolated (stand-alone) power system and micro grid. A small stand-alone power system can be found on offshore islands. Renewable energies will help reduce CO_x, SO_x, and NO_x emissions. In this project, the generation expansion planning for small stand-alone power system is considered.

Many alternative solutions could be used for this goal (decreasing the cost). Using renewable energy system is one of the possible solutions. A growing interest in renewable energy resources has been observed for several years, due to their pollution free energy, availability, and continuity. In practice, use of hybrid energy systems can be a viable way to achieve trade-off solutions in terms of costs. PV and Wind Generation (WG) units are the most promising technologies for supplying load in remote and rural regions. Therefore, in order to satisfy the load demand, hybrid energy systems are implemented to combine solar and wind energy units and to mitigate or even cancel out the power fluctuations. Energy storage technologies, such as Storage Batteries (SBs) can be employed. The proper size of storage system is site specific and depends on the amount of renewable energy generation and the load.

2. DATA GENERATION

There are three options in Data Synthesizer, specifically adapted for wind speed, Water availability, load, or solar radiation. There is no separate routine for synthesizing a temperature time series, but the load synthesizer may be used for that purpose. The underlying data synthesis method for all of the options, with some variations from one to another, is a Markov process approach. For wind speed, the method produces a time series with a specified mean, standard deviation, type of probability density function and autocorrelation. The load generator is similar to that for wind in that it results in a time series with a specified mean, maximum, minimum, probability density function and autocorrelation. Lastly, in the solar radiation synthesizer, the Data Synthesizer actually creates a time series of clearness indices. These are then multiplied by the extraterrestrial solar radiation to produce the solar radiation time series itself.

STEP 1: DATA INPUTS

For wind speed data generation, the inputs for the time series data synthesizer are the mean, standard deviation, type of probability density function, and autocorrelation at a specified lag. Note that if a Rayleigh distribution is selected, then only the desired mean is needed, since that case has a direct relation between the mean and the standard deviation. For the load synthesizer, the minimum and maximum values are used rather than the standard deviation. For solar data, the mean clearness index is the input to this part of the code. These values will then determine the characteristics of the probability density function and accordingly the probability density vector. For hourly water availability, the inputs for the data synthesizer are the mean, standard deviation, type of probability density function and autocorrelation at a specified lag. Here, Rayleigh distribution is selected, then only desired mean is needed for monthly data calculation of water availability.

STEP 2: MARKOV PROCESS TRANSITION PROBABILITY MATRIX

The method of generating a time series from a Markov process Transition Probability Matrix (TPM) is fairly well known. The method initially assumes that any time series can be represented by a sequence of "states." The number of states is chosen so that generated time series do not appear too discontinuous, and so 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 position in the matrix 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. One feature of a TPM is that the sum of all the values in a given row should equal 1.0. This corresponds to the fact that any succeeding point must lie in one of the states. 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. For example, suppose a time series with values between 0 and 50 were to be represented by 10 states.

The most intuitive and most common way to generate a Markov TPM is to start with a time series of data. Each successive pair of points is examined to see which states both are in. By tallying these, the number of times, and hence probability, that there is a "transition" from state- i to state-j can be determined. The result of this analysis for transitions from each state to each state yields all the values needed to fill in a TPM.

The data synthesis algorithm generates the TPM without the use of time series data. This is considerably less intuitive than the direct approach, but it is possible to do it 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 below. Since there is a direct relation to the probability density function and means and standard deviations, those values will be preserved as well.

A TPM can generate a time series which will have a mean, standard deviation and probability density function close to the target values. The time series will have an exponentially decreasing autocorrelation, but will not necessarily be equal to that of the target.

STEP 3: GENERATION OF TIME SERIES USING THE 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. For example, suppose a 5 x 5 TPM were being used, and that the state probabilities in the row of interest were 0, 0.2, 0.4, 0.3, and 0.1. Then, there would be a 20% chance that the next number would be in state-2, a 40% chance it would be in state-3, etc. Subsequent points are generated in an analogous way.

STEP 4: CALCULATION OF ACTUAL MEAN AND STANDARD DEVIATION OF TIME SERIES

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.

STEP 5: ADJUSTING TIME SERIES TO CORRECT MEAN AND STANDARD DEVIATION

The calculated mean is subtracted from each value of the first time series to obtain a new time series with 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.

STEP 6: DIURNAL SCALING OF TIME SERIES

It may be 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.

3. MARKOV MODEL

Markov Chain models are generally used for the generation of synthetic wind speed and wind power time series. The Markov approach is based on two hypotheses. Firstly, the prediction of the future states of a system, based on the present state alone, does not differ from that formulated on the basis of the whole history of the system. Secondly, when this transition probability does not depend on the age of the system (time), the Markov process is called homogeneous. In a homogeneous Markov process, the time between successive transitions has an exponential distribution.

The Markov approach is based on the following hypotheses:

- The prediction of the future states of a system, based on the present state alone, does not differ from that formulated on the basis of the whole history of the system. When this transition probability does not depend on the age of the system (time), the Markov process is called homogeneous.In a homogeneous Markov process, the time between successive transitions has an exponential distribution. In some applications, the modeling of the failure-repair process is based on the following hypotheses:
- The successive time-to-failure values are independent and identically distributed random variables. The successive time-to-repair (or recovery time) values are independent and identically distributed random variables.

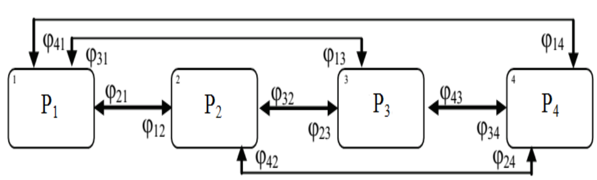

Fig.1:Markovian model with transitions among all states, N = 4

4. ALGORITHM & EQUATIONS

The complete process for synthesizing time series data is enumerated and illustrated below with an algorithm:

- Inputting the target parameters.
- Creating a Markov process transition probability matrix.
- Generating an initial time series using the Markov process transition probability matrix.
- Calculating the actual mean and standard deviation of the time series.
- Adjusting the time series if necessary to ensure that it has the desired mean and standard deviation.
- Multiplying the time series (when applicable) by a diurnally (or longer) varying scale factor.

a) Hourly Wind Speed Data:

Wind speed data is often modeled by the Weibull distribution, whose probability density function is given by:

$$p\,(V) = \left(\frac{k}{c}\right)\left(\frac{V}{c}\right)^{k-1} \exp\left(-\left(\frac{V}{c}\right)^{k}\right)$$

where c = scale factor (units of speed)
k = shape factor (dimensionless)

The Rayleigh distribution is also commonly used for wind speed. It is actually a subset of the Weibull, but with a constant relation between the mean and the standard deviation. Thus, only the mean needs to be specified. The Rayleigh probability density function is given by:

$$p\,(V) = \frac{\pi}{2}\left(\frac{V}{\vec{V}^2}\right) \exp\left(\frac{\pi}{2}\left(\frac{V}{\vec{V}}\right)^{2}\right)$$

where $\left(\vec{V}\right)$ = Long term mean

b) Hourly Solar Irradiation Data:

The extraterrestrial radiation, E0 is found from:
$E_0 = E_{sc}$ (1+0.033 cos (360*n/365)) [cos (φl) cos (δ) cos (ω) + sin (φl) sin (δ)]

Where E = mean solar irradiation
Esc =Solar constant (1367 W/m2)
φl = site latitude
δ = Sun's declination= 23.45* sin [(284+n)(360/365)] , deg
ω = hour angle at middle of time step, deg
n = Julian day

c) Hourly Load Data:

$$p(x) = \frac{\pi}{2}\left(\frac{x}{\vec{x}^2}\right) \exp\left(\frac{\pi}{2}\left(\frac{x}{\vec{x}}\right)^{2}\right)$$

Where x = L – Lmin, kW
Lmin = Minimum Load, kW
L = Instantaneous Load, kW

d) Reliability Indices

- Loss of Load Probability (LOLP) = (PF / e)

  where, PF = system failure probability
  e = Exposure factor
- Loss of Load Expectation (LOLE) = 365 * LOLP

- Loss of Load Frequency (LOLF) = Ff

  where, Ff = system failure frequency
- Loss of Load Duration (LOLD) = (LOLP/LOLF)
- Expected Energy Not Supplied (EENS) = ∑ Ci Fi Di

where,Ci = ith state capacity outage
Fi = ith state individual frequency
Di = ith state individual duration

- Energy Index of Reliability (EIR) is given by

  EIR = 1 – EENS(p.u)

5. RESULTS

In Table 5.1, data of the wind speeds (in meters per second) and irradiation (in watts per meter^2) and Water availability measured in 2007 for all each month is presented.

Month	Wind Speed (m/s)	Solar Irradiation (kWh/m2/d)	Clearness index (Kt)	Water availability (L/s)
January	3.8	2.6	0.54	18.1
February	5.0	3.4	0.55	17.0
March	5.6	5.3	0.69	22.1
April	5.9	5.8	0.58	24.2
May	6.2	6.1	0.55	24.2
June	7.2	7.4	0.64	28.8
July	5.4	7.2	0.66	30.0
August	5.6	7.1	0.70	29.1
September	6.6	6.5	0.77	26.0
October	6.2	6.0	0.88	24.2
November	4.8	4.6	0.90	24.2
December	3.3	2.1	0.44	20.0

Table.1: Weather Statistics for test system

Inputs to the software are mean solar irradiation, latitude of the site (23^0 47'), Average clearness index (k_T) and number of days. In Fig.2: the hourly solar irradiation obtained from the software is shown.

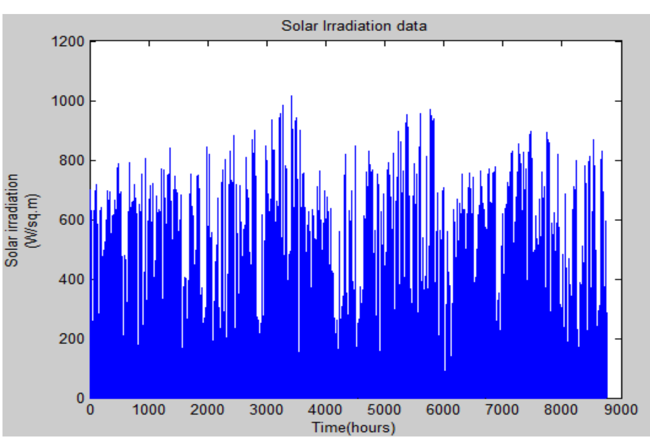

Fig.2: Hourly Solar Irradiation Data

In this project, for 10-kW WTG cut-in speed is 3 m/s, cut-out speed is 25 m/s and rated speed is 16 m/s. Hourly wind speed data obtained from data Synthesizer is shown in Fig.3

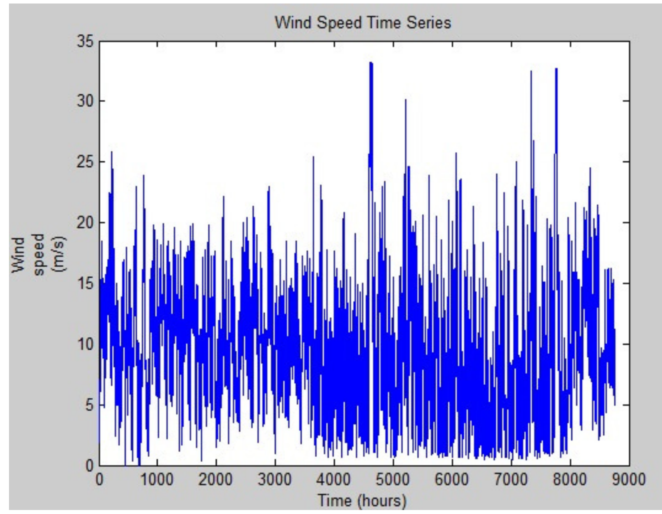

Fig.3: Hourly Wind Speed Data

In this,the inputs to the software are mean water availability, number of days and Rayleigh distribution. In fig.4.4 The hourly water availability obtained from the software is shown.

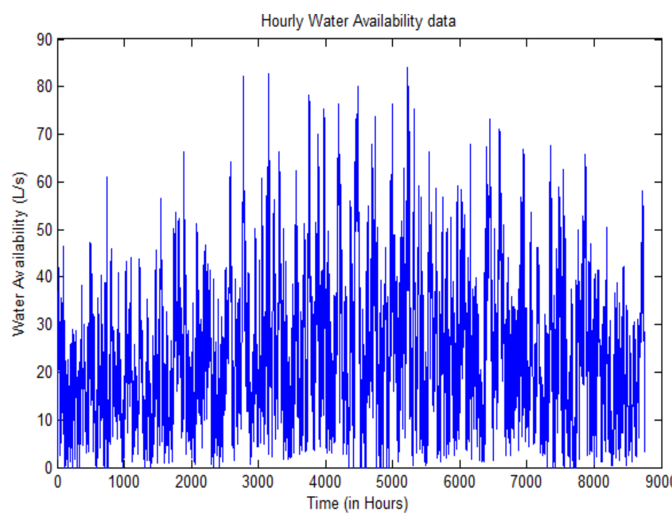

Fig.4: Hourly Water Availability

The Load profile utilized for the study of stand-alone power system is considered as:

Minimum Load = 5 kW,Maximum Load = 20 kW

Average load = 10 kW, In Fig.5, the hourly load data obtained from the software is shown.

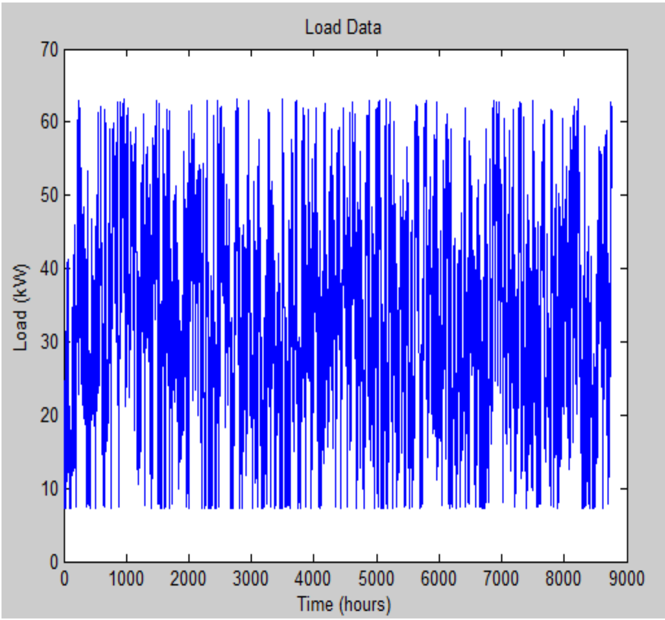

Fig.5: Hourly Load Data

Markov models accounting for transitions among all states:

a) Wind Markov Model:

In Table 4.6, the probability, frequency and duration of all the states for 13-state Wind Markov model are shown.

Table 4.6 Results of Wind Markov Model for all states

STATE	GENERATION (kW)	PROBABILITY	FREQUENCY (oc/h)	DURATION (h)
1	0-3.3	0.6817	0.0490	13.9207
2	3.3-6.6	0.2286	0.0655	3.4895
3	6.6-10	0.0896	0.0199	4.5115

Table.2: 3 state wind data generaion

b) Solar Markov Model:

In Table 4.7, the probability, frequency and duration of all the states for 3-state Solar Markov model are shown.

Table 4.7 Results of Solar Markov Model for all states

STATE	GENERATION (kW)	PROBABILITY	FREQUENCY (oc/h)	DURATION (h)
1	0-1.6	0.7209	0.0408	17.6891
2	1.6-3.2	0.1419	0.0741	1.9153
3	3.2-5.3	0.1372	0.0374	4.1024

Table.3: 3 state solar data generaion

c) Pico-Hydro Markov model:

In Table 4. the probability, frequency and duration of all states for 3-state hydro Markov model are shown. Table 4. Results of hydro Markov model for all states

STATE	GENERATION (Kw)	PROBABILITY	FREQUENCY (oc/h)	DURATION (h)
1	0-1.6	0.5994	0.0556	10.7823
2	1.6-3.2	0.3505	0.0664	5.2749
3	3.2-5.3	0.0501	0.0112	4.4796

Table.4: hydro data generation

d) Load Markov Model:

In Table 5, the probability, frequency and duration of all the states for 3-state Load Markov model are presented.Table 5 Results of Load Markov Model for all states

STATE	DEMAND (kW)	PROBABILITY	FREQUENCY (oc/h)	DURATION (h)
1	0-7	0.2908	0.0638	4.5554
2	7-14	0.4965	0.1068	4.6492
3	14-22	0.2127	0.0450	4.7259

Table.4: Weather Statistics for test system

e) Aggregate Markov Model:

In Table 6 the frequency and duration of all the states for 3-state Aggregate Markov model are shown.Table 6 Results of Aggregate Markov Model for all states from the above analysis, Reliability Assessment of small autonomous hybrid power system (SAHPS) is presented. Data Synthesizer software is used to determine the hourly wind speed, hourly solar irradiation, hourly water discharge and hourly load data from the monthly data of 1 year. Markov models for the WTG, PV, Pico-Hydro and system load with transitions among all states are established.

LOLP (days/yr)	LOLE (days/yr)	LOLF (occ/yr)	LOLD (days/occ)	EENS (MWh/yr)	EIR
0.1187	43.34	1.3291	0.0893	18.733	0.5143

Table.5: Combined wind-solar-hydro data generation

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