



Optimization and Reliability Evaluation of a Hybrid Power System

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Abstract— Because of the rapid consumption of conventional energy sources, renewable energy sources have become one of the important sources for electrical power generation. This paper considers wind-turbine generator, photo voltaic and Pico hydro generator as a small autonomous hybrid power system which acts as a distributed generation. The investment cost (installation and unit costs) is minimized using genetic algorithm to determine the number of WTG, PV and PHG units of SAHPS. For reliability evaluation of SAHPS, first the fuzzy-C-means (FCM) is employed to cluster the operation states for WTG, PV and PHG in 8760 h. then, the Aggregate and non aggregate Markov models for WTG, PV and PHG will be established to determine the 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), Availability and Unavailability of DG.

Keywords—Wind generation, Solar PV, Pico-Hydro, Data Synthesizer, Aggregate Markov model, Non-Aggregate Markov model, Reliability indices.

I. INTRODUCTION

Distributed Energy Resources have been considered as the important source of power generation, because of free availability of natural resources. In general, use of hybrid power systems 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 variations 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. Tahri et al. [1] presented optimization of Wind/PV/Diesel hybrid power system applied in term of technical and economic feasibility by simulation using HOMER. Ajay kumar et al. [2] have presented the optimal study of SAHPS using the techniques like Genetic Algorithm, Particle swarm optimization, Biogeography based optimization etc. Shamshad et al. [3] have presented the

algorithm to generate wind speed time series using first order and second order Markov models.

Karki and Billinton [4] presented an approach to capacity planning of small isolated systems, in which the conventional probabilistic and the well-being indices were used jointly. Diaf et al. [5] considered various types and capacities of system devices with configurations that can meet the desired system reliability by changing the type and size of the device systems. Manco and Testa [6] have presented the Markovian approach to model the power availability of wind turbine with transitions among all and contiguous states. Hong and Lian [7] have presented the optimal sizing of Wind/PV/Diesel generation using Markov Genetic algorithm. They discussed the Markov modeling of Distributed generation (DGs). Individual Markov models of generation and load is augmented to form aggregate and Non-Aggregate models [8].

In this paper, SAHPS is considered which consists of 10-kW Wind Turbine Generator (WTG), 5-kW Solar Photo-Voltaic (PV) unit and 5-kW Pico-Hydro unit. Data Synthesizer software [9] 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. Aggregate and Non-Aggregate Markov models are developed for the WTG, PV, Pico-Hydro and system Load. Reliability indices such as LOLP, LOLE, LOLD, LOLE, EENS and EIR are evaluated and analyzed.

II. MODELS

The objective is to evaluate the reliability indices for the Aggregate and Non-Aggregate Markov models of SAHPS.

A. Power Generations of Wind, Solar and Pico-Hydro unit

The weather statistics (wind speed, solar irradiation and water availability) of the test system should be taken into account for reliability assessment [1, 2]. Input data of the weather statistics of test system is shown in Table A1, given in Appendix. Specifications of Wind, Solar, Pico-Hydro and load models are shown in Tables A2, A3, A4 and A5 respectively.



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a) Wind Power model

Wind Power output equation [5] is given by

$$P_W = \begin{cases} 0, & V_W \leq V_C \text{ or } V_W \geq V_F \\ P_R * \left\{ \frac{(V_W - V_C)}{(V_R - V_C)} \right\}^3, & V_R \leq V_W \leq V_F \\ P_R, & V_R \leq V_W \leq V_F \end{cases} \quad (1)$$

where

V_C → Cutin speed (m/s)
 V_R → Rated speed (m/s)
 V_F → Cutout speed (m/s)
 P_R → Rated wind power (kW)

and

$$V_W = V_m * \left(\frac{H_h}{H_a} \right)^z \quad (2)$$

V_m → Measured wind speed
 H_h → Height of the hub of 10-kW WTG
 H_a → Height of the anemometer
 z → Friction coefficient for the ground

b) Solar Power Model

Solar Power output equation [5] is given by

$$P_{PV} = E * A_S * N_S * \eta \quad (3)$$

where,

E → Mean solar irradiation (W/ m²)
 A_S → Area of single module (m²)
 N_S → Number of solar modules
 η → Efficiency (%)

c) Pico-Hydro Power Model

Hydro Power output equation [2] is given by

$$P_h = \eta_h * \rho_w * g * H_h * Q_t \quad (4)$$

where

η_h → Efficiency of pico-hydro
 ρ_w → Density of water
 g → Acceleration due to gravity
 H_h → Effective head
 Q_t → Turbine flow rate

B. GENETIC ALGORITHM

The aforementioned problem can be formulated using the concept of chronological data including hourly load, wind speed, and irradiation/temperature as follows:

$$\text{Min } \{ N_W * (C_W^{\text{unit}} + C_W^{\text{in}}) + N_{pv} * (C_{pv}^{\text{unit}}) + N_W * (C_{ph}^{\text{unit}} + C_{ph}^{\text{in}}) + N_d * (C_d^{\text{unit}} + C_d^{\text{in}} + C_d^{\text{fuel}}) \} \quad (5)$$

Subject to

$$N_W^{\text{min}} \leq N_W \leq N_W^{\text{max}} \quad (6)$$

$$N_{pv}^{\text{min}} \leq N_{pv} \leq N_{pv}^{\text{max}} \quad (7)$$

$$N_{ph}^{\text{min}} \leq N_{ph} \leq N_{ph}^{\text{max}} \quad (8)$$

$$N_d^{\text{min}} \leq N_d \leq N_d^{\text{max}} \quad (9)$$

$$\text{LOLP} \leq \text{LOLP}^{\text{max}} \quad (10)$$

$$\text{CO}_2 \leq \text{CO}_2^{\text{max}} \quad (11)$$

where

N_W , N_{pv} , N_{ph} and N_d represent number of Wind units, Solar units, pico hydro units and Diesel units.

C_W^{unit} , C_{pv}^{unit} , C_{ph}^{unit} and C_d^{unit} denote the costs per unit (Rs./kW) for WTG, Solar, pico hydro and diesel units.

C_W^{in} → is the installation cost (Rs./kW) for the WTG.

C_d^{in} and C_d^{fuel} → are the installation (Rs./kW) and fuel costs for the diesel generator.

A penalty term is augmented to Eqn. (5) for further genetic selection. Specifically, the penalty function for dealing with Eqn. (10) is defined as follows:

$$P = PF^{(I/N_s)} \{ \text{LOLP} - \text{LOLP}^{\text{max}} \} \quad (12)$$

Where, PF is called the penalty factor in this project. Let the symbol I be the iterative index. Eqn. (12) implies that the penalty weight $PF^{(I/N_s)}$ should be gradually increased with less effect on the initial N_s iterations. The sign of the aforementioned penalty factor is positive.

C. FUZZY-C-MEANS (FCM) ALGORITHM

Traditional k-means clustering has at least the following disadvantages that were not considered in this project, as it does not yield the same result with each run and does not ensure that the result has a global minimum of variance. Hence, FCM is adopted herein. In FCM, each data has a degree (membership function) of belonging to clusters, rather than belonging completely to just one cluster. Bezdek [10] defined a function $J(U,V)$ as an objective in the FCM algorithm.

$$J(U,V) = \sum_{i=1}^M \sum_{c=1}^C (\mu_c(i))^m \|X_i - V_c\|^2, 1 \leq m < \infty \quad (13)$$

Where

C → is the clustering number
 M → represents the data number
 V_c → vector of the center in c^{th} cluster
 X_i → i^{th} data vector clustering
 $\mu_c(i)$ → membership function value as a weighting vector between V_c and X_i .

The clustering number is fixed for developing FCM. The value of 'C' depends on the user's requirement and the problem characteristics. When the value of $J(U, V)$ is minimized, the data vectors can be partitioned into clusters. Bezdek developed four solution steps to achieve the minimum as follows:

Step 1. Estimate a matrix of membership functions

$$U^{(k)} = [\mu_c(i)^{(k)}] \in R^{C \times N} \quad (14)$$

Where 'k' is the iterative index and $k = 0$ initially.

Step 2. Let $k = k + 1$. Compute the center of the c^{th} cluster.

$$V_c = \frac{\sum_{i=1}^M ((\mu_c(i)^{(k)})^m X_i)}{\sum_{i=1}^M (\mu_c(i)^{(k)})^m}, 1 \leq c \leq C \quad 1 \leq i \leq M. \quad (15)$$



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Step 3. Update $\mu_c(i)^{(k)}$ for all $X_i, i = 1, \dots, M$

$$\mu_c(i)^{(k)} = \frac{1}{\sum_{j=1}^C \left[\frac{\|X_i - V_c\|}{\|X_i - V_j\|} \right]^{\frac{2}{m-1}}}, \quad (16)$$

Step 4. If $\|\mu_c(i)^{(k)} - \mu_c(i)^{(k-1)}\| < \epsilon$, stop; else go to Step 2. The symbol ϵ is the convergence tolerance.

D. Reliability Indices

Reliability indices evaluated [8] are as follows:

- Loss of Load Probability (LOLP) is given by

$$LOLP = \frac{P_F}{e} \quad (17)$$

where, P_F = system failure probability
 e = Exposure factor

- Loss of Load Expectation (LOLE) is given by

$$LOLE = 365 * LOLP \quad (18)$$

- Loss of Load Frequency (LOLF) is given by

$$LOLF = F_f \quad (19)$$

where,

F_f = system failure frequency

- Loss of Load Duration (LOLD) is given by

$$LOLD = (LOLP / LOLF) \quad (20)$$

- Expected Energy Not Supplied (EENS) is given by

$$EENS = \sum_i C_i F_i D_i \quad (21)$$

where,

C_i = i^{th} state capacity outage

F_i = i^{th} state individual frequency

D_i = i^{th} state individual duration

- Energy Index of Reliability (EIR) is given by

$$EIR = 1 - EENS_{p.u.} \quad (22)$$

III. DATA GENERATION

In order to generate the Hourly Wind speed data, Hourly Solar irradiation data, Hourly water availability and Hourly Load data for a period of 1 year Data Synthesizer (DS) [9] software is used. It can be applied to wind speed, solar radiation, water availability, electrical load, or temperature.

The hourly wind speed is obtained from data synthesizer and is plotted in MATLAB which is shown in Fig. 1.

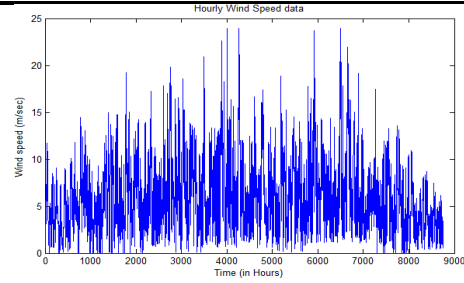


Fig. 1: Hourly wind speed data

The hourly solar irradiation is obtained from DS software and is plotted in MATLAB which is shown in Fig. 2.

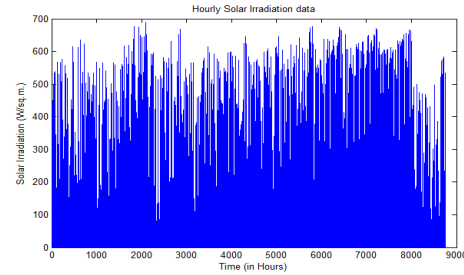


Fig. 2: Hourly Solar irradiation

The hourly water availability is obtained from DS software and is plotted in MATLAB which is shown in Fig. 3.

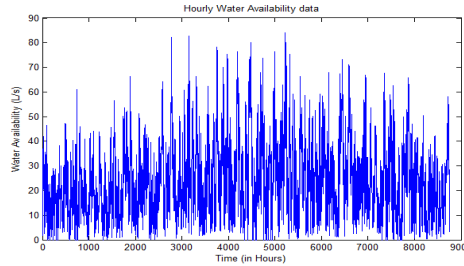


Fig. 3: Hourly Water availability

The hourly load data is obtained from Data synthesizer and is plotted in MATLAB which is shown in Fig. 4.

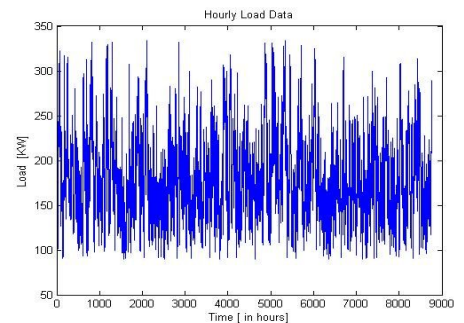


Fig. 4: Hourly Load data



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IV. MARKOV MODEL

Markov model is a state-space approach that can be applied to describe the process of the system through states.

The Markov approach [6] is based on the following assumptions:

- Prediction of the future states of a system is based on the present states only, but not on the past states.
- As the transitional probability doesn't depend on the history of the system, it is called as Homogeneous Markov process.

The probability of each class is given by

$$p(\cdot) = \frac{N(\cdot)}{N_T} \quad (23)$$

Case-(i): With Transitions among all states

A sample Markov model is shown in Fig. 5. Transition rates can be calculated as:

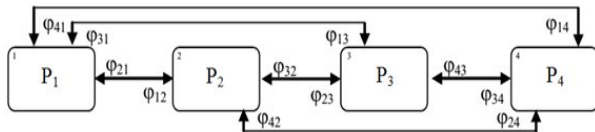


Fig. 5: Sample Markov model

$$\varphi_{ij \ i \neq j} = \frac{n_{ij}/N_T}{N_i/N_T} \cdot \frac{1}{\Delta t} = \frac{n_{ij}}{N_i} \quad (24)$$

$$\text{and } \varphi_{ii} = 1 - \sum \varphi_{ij \ i \neq j} \quad (25)$$

Case-(ii): With Transitions only among Contiguous states

The contiguous Markov model is shown in Fig. 6. Transition rates are given below:

$$\begin{aligned} \varphi'_{i,i+1} &= \sum_{j>i} \varphi_{ij} \\ \varphi'_{i,i-1} &= \sum_{j<i} \varphi_{ij} \\ \varphi'_{ij \ j \neq i-1, i+1} &= 0 \\ \varphi'_{ii} &= 1 - \sum \varphi_{ij \ i \neq j} \end{aligned} \quad (26)$$

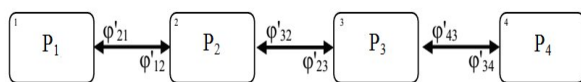


Fig. 6: Contiguous Markov model

The frequencies can be calculated as:

$$f_i = \alpha_i \cdot \sum_{j=1, j \neq i}^N \{\varphi_{ij}\}, \quad i = 1, 2, \dots, N \quad (27)$$

The mean state duration d_1, d_2, \dots, d_N can be obtained directly from transition rates as:

$$d_i = 1 / [\sum_{j=1, j \neq i}^N \{\varphi_{ij}\}], \quad i = 1, 2, \dots, N \quad (28)$$

A. Wind Markov Model

Hourly Wind power output has been obtained from the hourly wind speed by using equation 1 and the table 1 shows the wind power classification

Table 1: Wind power classification

Class Symbol	Power range (kW)	Samples in the class N (.)	Class probability p (.)
P _{w1}	[0-3.4822]	6122	0.6989
P _{w2}	[3.4822-7.5564]	2139	0.2442
P _{w3}	[7.5564-12]	499	0.0570

Case-(i):

The probability, frequency and duration of all the states are shown in Table 2:

Table 2: case-(i) solution for wind model

State	Probability	Frequency (oc/h)	Duration (h)
1	0.6989	0.0477	14.6459
2	0.2442	0.0602	4.0588
3	0.0570	0.0137	4.1583

Case-(ii):

Probability, Frequency and Duration of contiguous states is shown in Table 3:

Table 3: case-(ii) solution for wind model

State	Probability	Frequency (oc/h)	Duration (h)
1	0.6983	0.0477	14.6459
2	0.2469	0.0608	4.0588
3	0.0547	0.0132	4.1583

B. Solar Markov Model

Hourly solar power output has been obtained from the hourly solar irradiation by using equation 3 and the table 4 shows the solar power classification

Table 4: Solar power classification

Class Symbol	Power range (kW)	Samples in the class N (.)	Class probability p (.)
P _{PV1}	[0-2.0538]	6736	0.8666
P _{PV2}	[2.0538-3.9164]	1380	0.0908
P _{PV3}	[3.9164-5.3]	644	0.0426

Case-(i):

The probability, frequency and duration of all the states are shown in Table 5.

Table 5: case-(i) solution for Solar model

State	Probability	Frequency (oc/h)	Duration(h)
1	0.8666	0.0225	38.4914
2	0.0908	0.0375	2.4253
3	0.0426	0.0151	2.8246



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Case-(ii):

Probability, Frequency and Duration of contiguous states is shown in Table 6:

Table 6: case-(ii) solution for Solar model

State	Probability	Frequency (oc/h)	Duration (h)
1	0.8669	0.0225	38.4914
2	0.0909	0.0375	2.4253
3	0.0422	0.0149	2.8246

C. Hydro Markov Model

Hourly hydro power output has been obtained from the hourly wind speed by using equation 4 and the table 7 shows the hydro power classification

Table 7: Pico-Hydro power classes

Class Symbol	Power range (kW)	Samples in the class N (.)	Class probability p (.)
P _{h1}	[0-1.7163]	5618	0.6413
P _{h2}	[1.7163-3.1112]	2577	0.2942
P _{h3}	[3.1112-5.3]	565	0.0645

Case-(i):

Probability, frequency and duration of all states are shown in Table 8.

Table 8: case-(i) solution for Hydro model

State	Probability	Frequency (oc/h)	Duration (h)
1	0.6413	0.0519	12.3473
2	0.2942	0.0663	4.4355
3	0.0645	0.0148	4.3462

Case-(ii):

Probability, Frequency and Duration of contiguous states is shown in Table 9:

Table 9: case-(ii) solution for Hydro model

State	Probability	Frequency (oc/h)	Duration (h)
1	0.6401	0.0518	12.3473
2	0.2956	0.0666	4.4355
3	0.0643	0.0148	4.3462

D. Load Markov Model

In Table 10, load demand divided into three classes and corresponding number of samples and probability of the each class obtained from Fig. 4 are shown.

Table 10: Load Demand classes

Class Symbol	Demand (kW)	Samples in the class N (.)	Class probability p (.)
P _{L1}	[0-189.3052]	5451	0.6213
P _{L2}	[189.3052-258.0084]	2644	0.3021
P _{L3}	[258.084-400]	665	0.0766

Case-(i):

Probability, frequency and duration of all states are shown in Table 11.

Table 11: case-(i) solution for Load model

State	Probability	Frequency (oc/h)	Duration (h)
1	0.6213	0.0465	13.3603
2	0.3021	0.0601	5.0266
3	0.0766	0.0141	5.4508

Case-(ii):

Probability, Frequency and Duration of contiguous states are shown in Table 12:

Table 12: case-(ii) solution for Load model

State	Probability	Frequency (oc/h)	Duration (h)
1	0.6209	0.0465	13.3603
2	0.3034	0.0604	5.0266
3	0.0757	0.0139	5.4508

V. COMBINED GENERATION AND LOAD MODEL

Let 'C₀' be the total available capacity of the generating system. C_j = Available capacity of the ith combined state. In Fig. 7, the state space diagram of combined generation and load model [8] is presented.

N = utmost = 2ⁿ - 1

'n' number of units

The individual probability of the kth combined Generator and load state is

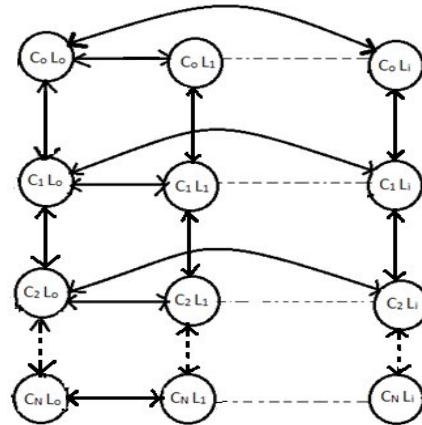


Fig 7: Combined Generation and Load model

$$p_k = p_{C_j} * p_{L_i} \quad (29)$$

Capacity margin is the difference between available Capacity (C_j) and the actual load (L_i).

If C_j > L_i, then capacity margin > 0 and this particular state is referred to as the Positive Margin state (PM state).

If C_j < L_i, then capacity margin < 0 and this particular state is referred to as the Negative Margin state (NM state).

➤ System failure probability is given by

$$P_f = \sum_{k \in NM} p_k \quad (30)$$



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The Transition rate from a given combined generator and load model state 'k' to any higher capacity state is given by $\mu_{k-H} = \mu_{cj-H} + \lambda_{Li-Lo}$ (33)

Similarly the transition rate from a given state to its lower capacity state is given by

$$\lambda_{k-L} = \lambda_{cj-L} + \lambda_{Lo-Li} \quad (31)$$

where, L- Lower capacity state
H- Higher capacity state

$$\lambda_{Li-Lo} = \frac{1}{MTTF} = \frac{1}{e*do}$$

$$\lambda_{Lo-Li} = \frac{1}{MTTR} = \frac{1}{(1-e)*do}$$

Frequency of failure of the system, f_k is given by

$$f_k = \sum_{k \in NM} (P_k * \sum_{s \in NM} (\mu_{k-s} + \lambda_{k-s})) \quad (32)$$

A. Aggregate Markov Model

The Aggregate Markov model is obtained from the individual Markov models of DGs with transitions among all states. The combined generation model is evaluated from probability, frequency and duration of WTG, PV and Pico-Hydro models.

From the 3-state wind, 3-state solar and 3-state Pico-hydro Markov models with transitions among all states a 27-state aggregate generation model is developed. Then aggregate generation model is combined with 3-state load model and 81-state Aggregate Markov model is developed and implemented in MATLAB.

The results summarized in Table 13, presents the reliability indices evaluated for this model:

Table 13: Results from Aggregate model

LOLP (days/yr)	0.4337
LOLE (days/yr)	158.3050
LOLF (occ/yr)	1.3512
LOLD (days/ occ)	0.3210
EENS (MWh/yr)	0.66190
EIR	0.5687
Availability	0.611685922
UnAvailability	0.38841408

B. Non-Aggregate Markov Model

The Non-Aggregate Markov model is obtained from the individual Markov models of DGs with transitions only among contiguous states. The combined generation model is evaluated from probability, frequency and duration of WTG, PV and Pico-Hydro models.

From the 3-state wind, 3-state solar and 3-state Pico-hydro Markov models with transitions among only contiguous states a 27-state non-aggregate generation model is developed. Then non-aggregate generation model is combined with 3-state load model and 81-state Non-Aggregate Markov model

is developed and implemented in MATLAB. The results summarized in Table 14, presents the reliability indices evaluated for this model:

Table 14: Results from Non-Aggregate model

LOLP (days/yr)	0.4328
LOLE (days/yr)	157.9753
LOLF (occ/yr)	1.3518
LOLD (days/ occ)	0.3202
EENS (MWh/yr)	0.66129
EIR	0.5691
Availability	0.612411449
UnAvailability	0.387488548

VI. CONCLUSIONS

In this paper, 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 and only among contiguous states are established. Aggregate and Non-Aggregate Markov models are developed from the individual Markov models. Reliability indices are evaluated for Aggregate and Non-Aggregate Markov models. For all the models MATLAB programs are developed and results are obtained. From the comparison of results, it is concluded that although both the methods yielding approximately same indices, non-Aggregate Markov model takes only a few transitions to contiguous adjacent states whereas Aggregate Markov model requires all possible transitions among all states. Memory required for contiguous states is less as compared to the aggregate model.

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BIOGRAPHIES



Srikanth Paleti was born in Kodad, India. He received his Bachelor's degree of Electrical and Electronics engineering in 2011 and post graduate student in Electrical power systems since 2012 in Anurag Engineering College Affiliated to JNT University, Hyderabad. His research interests in generation and distribution system reliability.



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S. Chandra Sekhar received his B.Tech and M.Tech (High Voltage Engineering) in Electrical & Electronics Engineering from 2001 and 2004. He is pursuing Ph.D at K L University. Presently he is working as associate professor and Head of the Department. His area of interest includes Micro Grids, High voltage transmission, Special Machines and Power Systems.