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Advanced Computation Method for Value-Based Distribution Systems Reliability Evaluation

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Presentation outlines

- Introductory background

Distribution systems

Reliability of distribution systems

Value based reliability

Assessment techniques

Aim of proposed technique

- Outlines of MLMC method
- Case studies
- Results and future works

Reliability of distribution system

- Definition

Interruption, customer satisfaction, continuity of supply

- Why need reliability analysis

Measuring past performance and predicting future performance
Improved system performance
Basis for designing new or expanded existing system planning
Maintenance scheduling and resource allocation

Value -based reliability index

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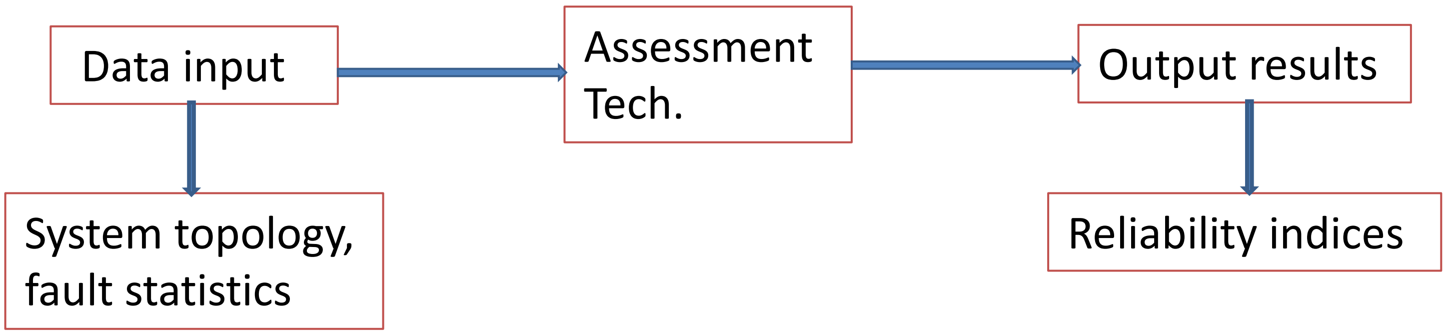
- Electric power business has changed dramatically for the past 30 years.

- There has been a considerable change in the structure and electric power system operation throughout the world.

- As the world gets more and more dependent on the electric power and since the reliability concerns have been increased, studying power interruptions and their economic worth attracts more attention.

- Worth of reliability in terms of customer expected cost of interruption (ECOST)

Assessment data



General block diagram of reliability analysis

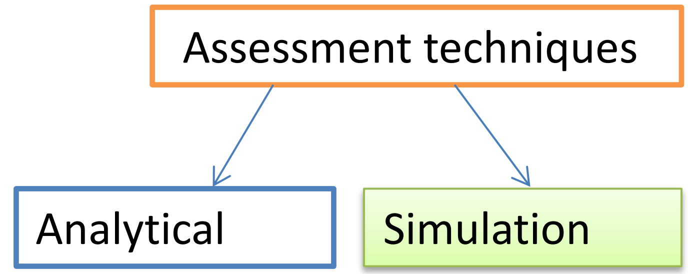
- Inputs

System topology (distribution feeder)

System information (Loads, customers, repair time)

Fault statistics (Number of faults, failed element, failure rate, location)

Assessment techniques



Analytic technique- just provide expected or average value of the worth index from historic data
Actual shape of the statistical distribution associated with the index is not considered

MCS - variation of the index (prediction of uncertainty/actual behaviour over the time)

Monte Carlo Simulation

In MC simulation we estimate the expectation using

$$\hat{E}_{MC}[R_a] = \frac{1}{N_{MC}} \sum_{i=1}^{N_{MC}} R_a^{(i)}$$

Two sources of error here:

Sampling error due to the finite number of samples

Bias error because Ra is an approximate of R

Monte Carlo Simulation

MSE is used to measure the accuracy of the MC estimator.

$$MSE = N_{MC}^{-1} V[R_a] + [E(R_a - R)]^2$$

To achieve RMSE of ε requires:

$N_{MC} = O(\varepsilon^{-2})$

bias = $O(\varepsilon)$

In the case of a very reliable system, a large number of samples is required to satisfy the given accuracy level.

Proposed method

Reducing computational cost of reliability evaluation by MLMC

What is the basic difference between MCS and MLMC?

M. B. Giles, “Multilevel Monte Carlo methods,” *Acta Numerica,* vol. 24, pp. 259-328, 2015.

Two level Monte Carlo

In a SDE simulation, if we want to estimate $E[R_1]$, it is much cheaper to simulate using $[R_0]$

Since $R_0 \sim R_1$

$$E[R_1] = E[R_0] + E[R_1 - R_0]$$

Estimator:

$$\frac{1}{N_0}\sum_{i=1}^{N_0} R_0 + \frac{1}{N_l}\sum_{i=1}^{N_l}(R_1 - R_0)$$

Advantage: if $[R_1 - R_0]$ is small, no need many samples to accurately estimate

$E[R_1 - R_0]$, so cost will be reduced greatly.

Basics of MLMC

Consider MC simulation with different levels, $l = 0, 1, 2, \dots \dots L$

$$E[R_L] = E[R_0] + \sum_{l=1}^{L} E[R_l - R_{l-1}]$$

Expected value is same – aim is to reduce variance of estimator

Idea is to independently estimate each of the terms on the R.H.S., in a way which minimises the overall variance for a given accuracy.

Finest level is still the same, but will use very few samples at that level.

Basics of MLMC

$$E[R_L] = E[R_0] + \sum_{l=1}^{L} E[R_l^f - R_l^c]$$

$$\widehat{\mathbb{E}}_{ML}[R_a] = \sum_{\ell=0}^{L} \frac{1}{N_\ell} \sum_{i=1}^{N_\ell} \left[R_\ell^{(i)} - R_{\ell-1}^{(i)}\right].$$

$$N_l = 2\varepsilon^{-2}\sqrt{V_l/C_l}\left(\sum_{l=0}^{L}\sqrt{V_l C_l}\right).$$

R_l^f=Fine path estimator having timestep size $h_f = 2^{-l}T$

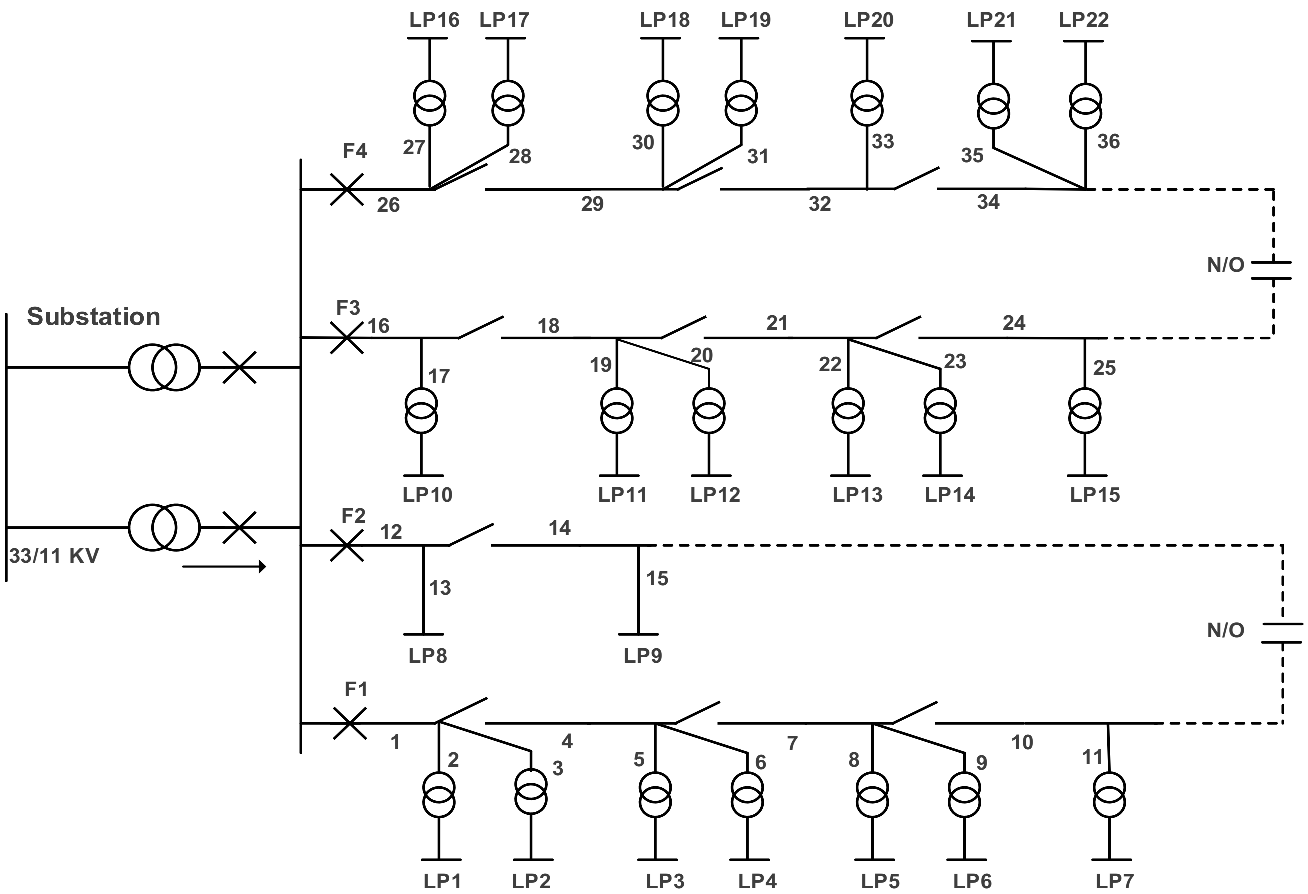
R_l^c=Coarse path estimator having timestep size $h_c = 2^{-(l-1)}T$

As level increases and the grid resolution becomes finer, the require timesteps or time increase

Case studies

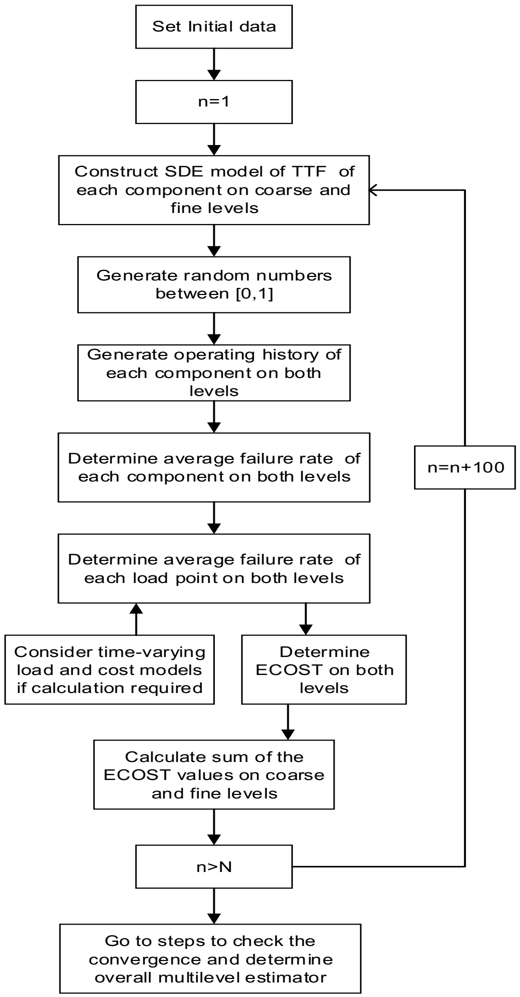
1. Network, reliability data
2. Component modeling and Up time history
3. SDE modelling
4. Load and cost models
5. Reliability indices calculation
6. Results

Test system

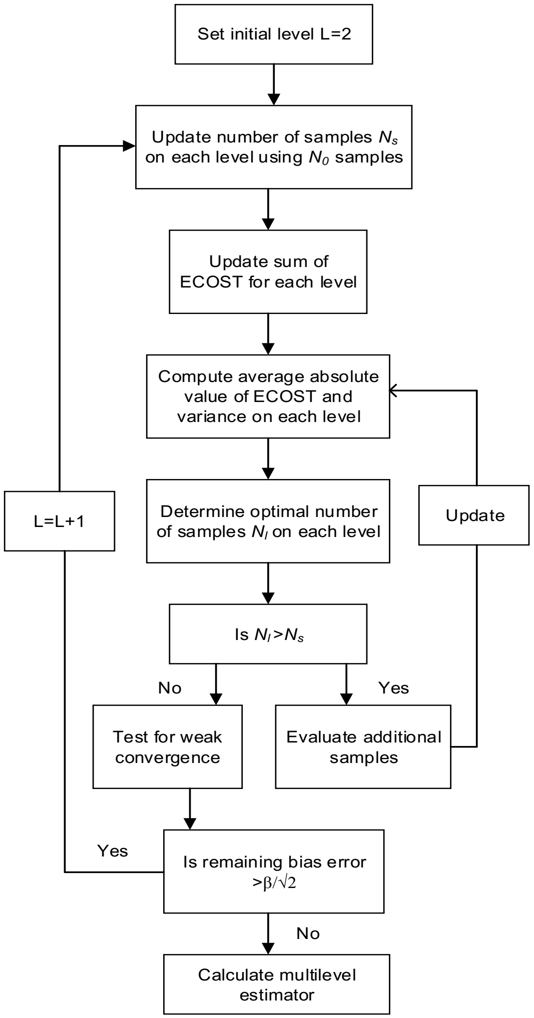


Distribution system of RBTS bus 2

Flowchart



(a) ECOST estimation on coarse and fine levels



(b) Convergence test

SDE

$$dS_t = \mu(S_t, t)dt + \sigma(S_t, t)dW \quad 0 < t < T$$

(deterministic changes + random changes)

μ= Rate of change of average value of stochastic process (drift)
σ= Degree of variation of stochastic process over time (volatility)

dW=Brownian motion

Solution: Milstein discretisation

$$\mathrm{S_{m+1} = S_m + \mu(S_m, t_m)h + \sigma(S_m, t_m)\Delta W_m + \frac{1}{2}\sigma^2(S_m, t_m)(\Delta W_m^2 - h)},$$

step size $h = {}^{T}/_{n}$, *n* timesteps and Brownian increments ΔW_m

$n = 2^l$and l is called the level

Oksendal, B. *Stochastic differential equations: an introduction with applications*. Springer Science & Business Media, 2013.

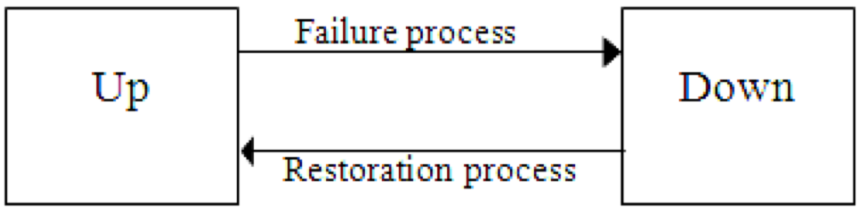
Harrison, J. Michael. *Brownian motion and stochastic flow systems*. New York: Wiley, 1985.

SDE modelling

Construct SDE models of TTF at levels $l = 0$ and $l > 0$

$$S_{\lambda i}^{c} = S_{\lambda i}^{c} + \mu S_{\lambda i}^{c} h_c + \sigma S_{\lambda i}^{c} dW_c + \frac{1}{2}\sigma^2 S_{\lambda i}^{c}({dW_c}^2 - h_c),$$

$$S_{\lambda i}^{f} = S_{\lambda i}^{f} + \mu S_{\lambda i}^{f} h_f + \sigma S_{\lambda i}^{f} dW_f + \frac{1}{2}\sigma^2 S_{\lambda i}^{f}({dW_f}^2 - h_f),$$



Operating history of component i:

$$T_{ui} = -S_{\lambda i(m+1)}\, ln(U)$$

Load and cost modelling

For a supply point p:

$$L_p = L_{peak} \times W_p \times D_p \times \frac{\sum_{t=ts}^{te} H_P(t)}{te-ts+1}, \text{ MW}$$

Annual peak load (L_{peak}), weekly peak load as a percentage of annual peak (W_p), daily peak load as a percentage of weekly peak (D_p) and hourly peak load as a percentage of daily peak (H_p)

$$C_p = C_{avg} \times \frac{\sum_{t=ts}^{te} W_p}{te-ts+1}, \text{ (\$/kW)}$$

Sector customer damage function (SCDF) [9] is analyzed to found the cost (C_p) related to a load point P interruption for a duration r_p

Direct evaluation of ECOST is very difficult, is to evaluate the impacts and losses incurred by customers due to power supply failures

System ECOST

Average failure rate for component i:

$$B_i = \frac{M}{\sum_{n=1}^{N} T_{ui}}, \text{ (occ./yr)}$$

M is the number of times component i fails during whole simulation period and N is the desired number of simulated periods.

Average failure rate for load point p:

$$F_p = \sum_{i=1}^{n_i} B_i, \text{ (occ./yr)}$$

n_i denotes the number of outage events interrupting the service of the load point P

System ECOST:

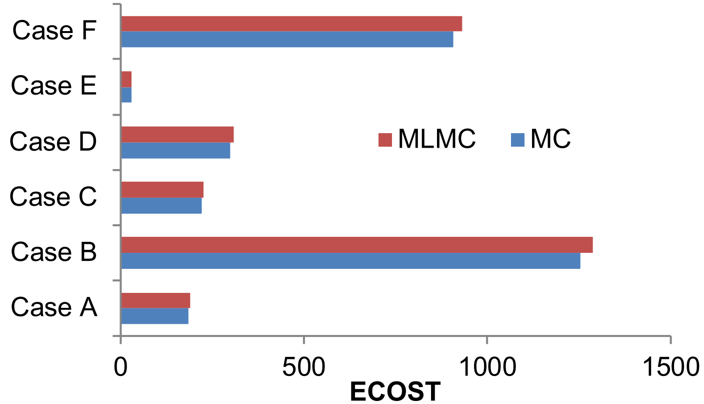
$$ECOST = \sum_{p=1}^{n_p} F_p L_p C_p. \text{ (k\$/yr)}$$

n_p is the total number of supply points in the system.

Test results

Case studies for network reinforcement effect analysis

Case	Disconnecting Switches	Fuses	Alternative Supply	Transformer Action Restoration
A	Yes	Yes	Yes	Repairing
B	No	No	No	Repairing
C	No	Yes	No	Repairing
D	Yes	No	Yes	Repairing
E	Yes	Yes	Yes	Replacement
F	Yes	No	No	Repairing



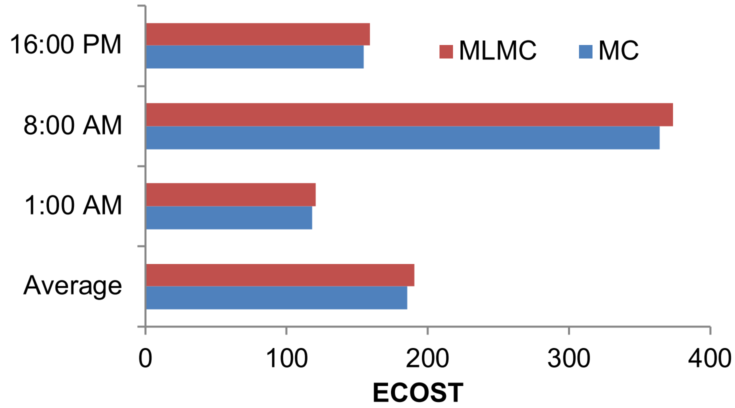
ECOST (k$/yr) variation due to network reinforcement

Effect of network reinforcement on cost estimation time

Method	Case A	Case B	Case C	Case D	Case E	Case F
MC (s)	35.23	1110.13	49.67	80.19	0.92	317.25
MLMC (s)	1.14	48.19	1.71	2.76	0.032	25.15

Test results

ECOST (k$/yr) variation due to time-varying load and cost models

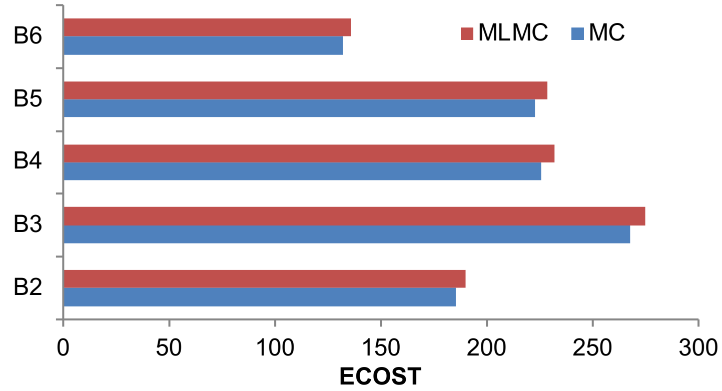


Effect of time-varying load and cost models on computation time

Method	Average	1:00 AM	8:00 AM	16:00 PM
MC (s)	35.23	15.87	134.37	25.43
MLMC (s)	1.14	0.51	5.04	0.87

Test results

ECOST (k$/yr) variation due to network size and load types



Effect of network size and load types on computation time

Method	B2	B3	B4	B5	B6
MC (s)	35.23	69.27	49.33	47.40	27.06
MLMC (s)	1.14	3.65	1.85	1.58	0.9

Reduced samples

Number of samples vs Level

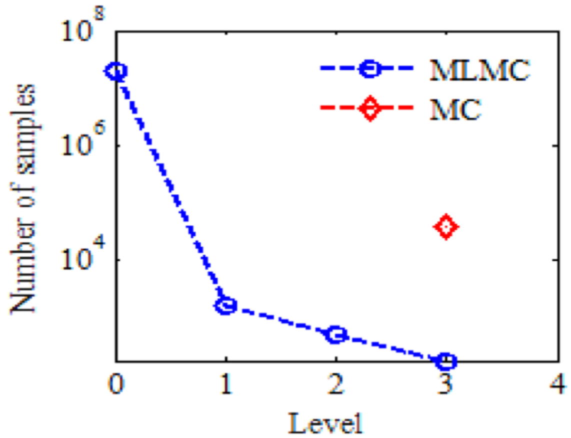


Fig. Required number of samples for convergence [Case A] at each level of MLMC and MCS

MLMC	124238	13003	6268	2262
MC	15000			

Summary

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- Achieved desired accuracy and saving of cost using multilevel Monte Carlo method
- MLMC is simple and interesting, but key challenge is how to apply it in reliability analysis
- Can easily be expanded in future work to include additional factors such as weather dependent failure and repair models and integration of distributed generation.
- Distribution system planning and design engineers could predict accurate reliability indices with accelerating the process.

Q/A