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EFFECTIVENESS OF OPTIMUM STRATIFIED SAMPLING IN MONTE CARLO CHRONOLOGICAL CO_2 EMISSION POLLUTANTS OF GENERATION SYSTEM MODELING

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Abstract – This paper presents a combined Monte Carlo and stratified–sampling method to better estimate CO_2 emissions for generation systems. This design seeks to enhance the precision of CO_2 emission pollutants in generation system estimation, while reducing computation time. The techniques included are optimum stratified sampling and proportional estimate. The optimum stratification rule aims to remove any judgmental input and to render the stratification process *entirely mechanistic. The estimator, provided by proportional* statistics of the sample, can avoid identification of the regression model and thus save computation time. Hence, the effectiveness on precision improvement is demonstrated in this paper.

Keyword: CO_2 Emission Pollutants of Generation System Simulation, Monte Carlo Simulation, Stratified Sampling, Proportional Estimate

1. INTRODUCTION

Simulating the CO_2 emission pollutants of generation system is a very important part of power system generation planning [1~4] and greenhouse effect study [5]. Currently, there are two approaches to probabilistic CO_2 emission pollutants of generation system simulation: analytical and Monte Carlo simulations. The basic element of analytical approach [6~14] is a convolution process which entails the probability distribution of load and the generating outage capacity of random variables. The load probability is represented by a load duration curve which is attained by simply sorting and ordering the hourly load magnitude. This approach is efficient in computing, and well adopted by utilities. However, the load sorting process destroys its chronological information, and therefore incurs difficulties in simulating the chronological constraints often imposed in generation scheduling, thus resulting in an underestimation of CO_2 emission pollutants of generation system.

In the Monte Carlo simulation [15~19], a large population of trial system states are specified by random draws designed to capture the outage characteristics of the system generating units. Each trial system state represents one possible realization of hourly up/down status in the system generating units throughout the simulation period. The CO_2 emission pollutants of generation system is estimated by applying the unit commitment, including economic dispatch, to the sample of state population. In this approach, the chronology of load and power generation is preserved.

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However, sampling introduces imprecision in the estimation of CO_2 emission pollutants of generation system. To enhance the precision or to reduce the estimation variance, a Monte Carlo CO_2 emission pollutants of generation system simulation algorithm which combines variance reduction technique is proposed.

In section 2, a simulation process for the Monte Carlo CO_2 emission pollutants of generation system is described. Our proposed stratified sampling, and the proportional estimator are presented in sections 3 through 4. Computer implementation and numerical tests of our algorithm on the evaluation of CO_2 emission pollutants of generation system is discussed in sections 5 through 6.

2. PROBLEM DESCRIPTION

2.1 Generating Units' Outage Combinations

Assume the simulation period is comprised of total M weeks. In the uptime/downtime approach, any specified state is formulated into the following matrix form (with dimension of J×T and s_{jt} as the matrix elements) :

$$s = [s_{jt}] \tag{1}$$

where
- J total number of generating units
- T total number of hours (T = M×168)
- j generating units (j=1, 2, ...,J)
- t chronological hours (t=1, 2, ...,T)
- S_{jt} up (s_{jt}=1) or down (s_{jt}=0) status of unit j at hour t.

Let S denote a population of N system states specified above by random draws:

$$S = \{s_1, s_2, ..., s_N\} \tag{2}$$

2.2 Monte Carlo Simulation for CO_2 Emission Pollutants Estimation

For each specified state, one can apply the energy output of unit commitment to calculate the CO_2 emission pollutants value. Let $z_1, z_2, ..., z_N$, denote the CO_2 pollutants emission values to evaluate on $s_1, s_2, ..., s_N$, respectively, then let

$$Z = \{z_1, z_2, ..., z_N\}. \tag{3}$$

For an extremely large population size N, it is reasonable to assume that the population mean ($\overline{Z}$) is close to the true CO_2 emission pollutants value. As stated in section 1, for computational efficiency, only n (with n << N) sample states within S are evaluated by unit commitment in the Monte Carlo simulation to estimate $\overline{Z}$. To help sampling and estimation, the deterministic load duration curve type of simulator is applied. This simulator is a simple and common CO_2 emission pollutants of generation system technique and will be hereafter called the LDC technique [17]. Let y_1, y_2,

$\ldots, y_N$ be the CO_2 values to be calculated, and let

$$Y = \{y_1, y_2, \ldots, y_N\}. \quad (4)$$

On basis of Y, the desired n states are sampled from S, and evaluated by unit commitment for their z values. With these z's and Y known, $\overline{Z}$ is then estimated.

3. OPTIMUM STRATIFICATION

3.1 Basic Concept

Following the stratified sampling theory [20], population S is divided into L nonoverlapping subpopulations, called strata. Then L simple random samples are drawn independently from the individual strata. To explain, let $N_1, N_2, \ldots, N_L$ denote the L stratum sizes, and $n_1, n_2, \ldots, n_L$, their corresponding sample sizes. Thus N and n defined in section 2 can be expressed as

$$N = N_1 + N_2 + \ldots + N_L, \text{ and}$$
$$n = n_1 + n_2 + \ldots + n_L. \quad (5)$$

Now, let $\overline{y}_{sk}$ denote the sample mean for a simple random sample drawn out of stratum k, where k=1, 2, ..., L, and let $\overline{y}_{ss}$ denote the corresponding estimate of population mean ($\overline{Y}$) by stratified sampling. Then, calculate $\overline{y}_{ss}$:

$$\overline{y}_{ss} = \frac{\sum_{k=1}^{L} N_k \overline{y}_{sk}}{N} = \sum_{k=1}^{L} W_k \overline{y}_{sk} \quad (6)$$

Assume S is a heterogeneous population. Through stratification of S into strata, each being homogeneous internally, the variance of $\overline{y}_{ss}$, denoted by $V(\overline{y}_{ss})$, can be reduced [20]. The variance of estimate $\overline{y}_{ss}$ is found to be

$$V(\overline{y}_{ss}) = (1/n) \cdot \left(\sum_{k=1}^{L} W_k \sigma_k^2\right) \quad (7)$$

3.2 Proposed Stratification Process

Our proposed stratification process comprises of two major steps:
(1) determination of stratum number L, and
(2) construction of the L strata.
Both will be presented below.

(1) Construction of strata

To construct the strata for population Y, one needs to arrange variable y into ascending order. Methods for finding the best stratum boundaries have been derived by minimizing $V(\overline{y}_{ss})$ [20~24]. Among them, the cum$\sqrt[3]{f}$ rule, due to Ravindra Singh [24], is adopted in our proposed algorithm.

Given the frequency distribution of y, denoted by f(y), the cum$\sqrt[3]{f}$ rule is to form the cumulative of $\sqrt[3]{f(y)}$. Choose y_k so that they create equal intervals on the cum$\sqrt[3]{f}$ scale. Table 1 illustrates the rule applied to an example problem to be detailed in section 6. In this example, N=20 and the population members (y's) refer to the CO_2 emissions evaluated by the LDC technique specified in section 2. Refer to Table 1, $y_1=5.8395\times10^5$ MT and $y_N=6.1438\times10^5$ MT. Assume L=4. Following the cum$\sqrt[3]{f}$ rule, an equal interval on the cum$\sqrt[3]{f(y)}$ scale can be calculated as 12.444/4=3.111, which yields the stratum boundaries in Table 2.

(2) Number of strata

The number of strata can be obtained by observing the reduction in variance affected by the addition of the another stratum. That is, the variance from L strata is compared with the variance resulting from L−1 strata $(V(\overline{y}_{ss})_{L-1}/V(\overline{y}_{ss})_L)$. Reference [20] suggests that the number of strata (L) is selected at the lowest decreasing rate of $V(\overline{y}_{ss})$. However, at this stratification stage, the sample size n has not been decided yet. Thus without sampling, L is selected in our algorithm at the lowest VDR_L defined as:

$$VDR_L = \sum_{k=1}^{L-1} W_k^2\sigma_k^2 / \sum_{k=1}^{L} W_k^2\sigma_k^2 \quad (8)$$

In our algorithm, VDR_L is evaluated iteratively, i.e., L=2 at the first iteration, and L=L+1 in the subsequent iterations. For Table 1, the selected L by evaluating VDR_L is 4, where $\sum_{k=1}^{4} W_k^2\sigma_k^2 = (3^2\cdot7.5809\times10^6 + 6^2\cdot6.3149\times10^6 + 7^2\cdot8.6988\times10^6 + 4^2\cdot7.6510\times10^6)/20^2$ (see Table 3).

Table 1 Stratification by cum$\sqrt[3]{f}$ rule applied to example problem

CO_2 emission $10^5\times$MT	Frequency f	$\sqrt[3]{f}$	cum$\sqrt[3]{f}$
5.839566~5.869987	2	1.25992	1.25992
5.869987~5.900409	1	1.0	2.25992
5.900409~5.930830	1	1.0	3.25992
5.930830~5.961252	2	1.25992	4.51984
5.961252~5.991673	3	1.44225	5.96209
5.991673~6.022094	3	1.44225	7.40434
6.022094~6.052516	2	1.25992	8.66426
6.052516~6.082937	2	1.25992	9.92418
6.082937~6.113358	2	1.25992	11.18420
6.113359~6.143774	2	1.25992	12.44402

Remarks : (a) Unit of measurement : Metric ton(MT)
(b) CO_2 released due to fuel consumption :
0.3825 MT/Gcal for coal and
0.3149 MT/Gcal for oil
(c) CPU time:0.002sec (on SUN 4/60 Workstation)

Table 2 Stratum boundaries evaluated by the cum$\sqrt[3]{f}$ rule of the example problem in Table 1

Stratum code : k	Interval : $10^5\times$MT	Variance(σ^2_k) : ($10^6\times$MT^2)	Frequence : N_k
1	5.839566~5.900409	7.58088	3
2	5.900409~5.991673	6.31492	6
3	5.991673~6.052516	8.69884	7
4	6.052516~6.143774	7.65989	4

3.3 Stratification After Selection of the Sample

3.3.1 Sample Size (n)

Given a total sample size n, the proportional allocation yields $V(\bar{y}_{st})$ [20]:

$$V(\bar{y}_{st})_N=\frac{1}{n}\sum_{k=1}^{L}W_k\sigma_k^2 \tag{9}$$

where $W_k=N_k/N$ as defined in Eq. (6). In our algorithm, Eq. (9) is applied to the selection of sample size n at a pre–designated estimation precision (i.e. $V(\bar{y}_{st})$ denoted by V in Eq. (7)), shown as follows:

$$n=\frac{\sum_{k=1}^{L}W_k\sigma_k^2}{V}. \tag{10}$$

3.3.2 Optimum Sampling Allocation (n_k)

In stratification sampling, the values of the sample sizes (n_k) in the respective strata are chosen by the sampler. Proportional allocation, as used by Monte Carlo production simulation is adopted by our algorithm to decide the population sample size (n) at a pre–specified estimation precision (i.e., $V(\bar{y}_{st})$). Then the proportional allocation [19] is followed for the choice of n_h:

$$n_k=n\cdot\frac{W_k\sigma_k}{\sum_{k=1}^{L}W_k\sigma_k} \tag{11}$$

With n_k known for k=1, 2, ⋯, L, a random sample is drawn from each individual stratum to complete the sampling process. Take the example problem in Table 1 for demonstration. With the $V(\bar{y}_{st})$ pre–specified at 1.268×10^6 MT^2, a sample size n=6 is calculated by substituting both N_k and σ_k of Table 3 into Eq. (10). Then sample sizes (n_k) are calculated from Eq. (11), which yield $n_1=1$, $n_2=2$, $n_3=2$, and $n_4=1$(see Table 4).

4. PROPOSED ESTIMATION BY PROPORTIONAL ESTIMATE

In the proportional estimate method, an auxiliary variate Y correlated with Z is obtained for each unit in the sample. Following the proportional estimate, the estimate of the mean of population Z, denoted by $\bar{z}_{st}$ [20], is expressed by

$$\bar{z}_{st}=\sum_{k=1}^{L}w_k\bar{z}_{sk} \tag{12}$$

Table 3 Select number of strata by stratified population variances of the example problem

Number of strata(L)	Variance ($10^6\times MT^2$)	Variance decreasing rate (VDR_L)
1	72.35289	
2	13.48301	5.366
3	4.504320	2.993
4	3.646050	1.235
5	1.093280	3.335
6	1.056000	1.035

where $w_k=n_k/n$ is the weight of stratum k, $\bar{z}_{sk}=(1/n_k)\cdot\sum_{i=1}^{n_{ki}}z_{ki}$ is the estimate of stratum mean of stratum k. For the same problem as the proceeding sections, the estimated stratum means and population mean are tabulated in Table 5.

5. STEP–BY–STEP DESCRIPTION OF PROPOSED ALGORITHM

To save computer storage, the simulation is implemented on a weekly basis. Computational procedures for the M weekly simulations are generally the same, and each consists of five stages of computation: (1) Monte Carlo simulation for simulating generating units' outage combinations; (2) approximate generation scheduling; (3) stratified sampling; (4) unit commitment including economic dispatch; (5) mean estimation.

5.1 Monte Carlo Simulation

Because the simulation period under evaluation usually leads the present time by months or even by years, the random number generator (RNG) used to decide units' up/down status at hour t=1 will be different from those at t=2, 3, ..., T. The former is evaluated by the forced outage rate (FOR), the latter is by the mean–time–to–failure (MTTF) and the mean–time–to–repair (MTTR). The following descriptions indicate the Markov process mentioned in subsection 2.2 for the state formulation of the first week (denoted by m=1).

Step 1: Let j=1 (namely, the first unit)

Step 2: Let t=1 (namely, the first hour)

Step 3: Generate a random number $R_1\in[0,1]$ by the uniformly distributed random number generator. If $R_1<FOR$, set $s_{jt}=0$ (i.e., under repair); otherwise, $s_{jt}=1$ (i.e., being available).

Step 4: If $s_{jt}=1$, set parameter μ_j = $MTTF_j$ for unit j; otherwise, set $\mu_j=MTTR_j$.

Step 5: Generate a random number Δt by the exponentially distributed RNG with its mean at μ_j

$$\Delta t=(-1/\mu_j)\cdot\ln(R_2)$$

where $R_2\in[0,1]$ is a uniformly distributed random number.

Table 4 Sample size allocation of the example problem

Stratum code, k	Interval, $10^5\times MT$	Weight, (W_k)	Straum mean, ($\bar{y}_k$, 10^5MT)	Variance, (10^6MT^2)	Sample size, (n_k)
1	5.8396~5.9004	3/20	5.8625157	7.58088	1
2	5.9004~5.9917	6/20	5.9603780	6.31492	2
3	5.9917~6.0525	7/20	6.0320344	8.69884	2
4	6.0525~6.1438	4/20	6.1140358	7.65989	1

Table 5 Population mean estimation of the example problem

Strutum code, k	Sample size, (n_{ki})	Sample unit, (z_{ki})	Estimated stratum mean($\bar{z}_{sk}$, $10^5\times MT$)	Weight, (w_k)	Estimated population Mean ($\bar{z}_{st}$, $10^5\times MT$)
1	1	5.95674	5.95674	1/6	6.0994
2	2	6.03839 6.04064	6.03952	2/6	
3	2	6.15699 6.18169	6.16934	2/6	
4	1	6.22195	6.22195	1/6	

Step 6: Round off Δt into an integer number. Let $t=t+\Delta t$ and change the status of s_{jt}.

Step 7: If $t<168$, go to step 4; otherwise, record t and s_{jt} as $t^{(record)}$ and $s_{jt}^{(record)}$.

Step 8: Let $j=j+1$ (referring to the next unit). If $j \leq J$, go to step 2; otherwise, stop.

State formulation for the remaining weeks ($m=2, 3, \ldots, M$) follows the same procedure as above except steps 2, 3, and 7 revised as below:

Step 2: Let $t=t^{(record)}$.

Step 3: Let $s_{jt}=s_{jt}^{(record)}$.

Step 7: If $t < 168 \times m$, go to step 4; otherwise, record t and s_{jt} as $t^{(record)}$ and $s_{jt}^{(record)}$.

One iteration of the above procedure can generate one trial state, and N iterations provide the needed N trial states. Because only t's and s_{jt}'s in steps 2, 3, and 6 are recorded, computer memory required for storage of the N units' up/down tables is limited very much.

5.2 Approximate Generation Scheduling

For each of the N states, the LDC scheduler, schedules the generation of system generating units. This scheduler loads the system generating units in accordance with the priority list of the units' average incremental costs. For each hour t, subtract the maximum generation of units j's with $s_{jt}=1$ by the merit-order until the total system load is met. This subtraction process is repeated for all the N state combinations to attain N generation schedules.

With the generation known, the CO_2 emission pollutants emission for each of N state combinations can be found. After application of this approximation procedure to CO_2 emission pollutants of generation system are calculated, a population consisting of N trial cases is obtained.

5.3 Stratified Random Sampling

The following stratified random sampling is applied to the CO_2 emission pollutants of generation system population evaluated by the approximate LDC scheduler.

Step 1: Arrange y's into ascending order.
Step 2: Let the number of strata $L=2$.
Step 3: Construct strata by the cum$\sqrt[3]{f}$ rule presented in section 3.2

Table 6 Mean and variance of production CO_2 emissions evaluated by load duration curve and unit commitment on state formulation by MTTF/MTTR process

State formulation by evaluation iteams		CO_2
LDC*	population mean($\overline{Y}$)	6.010566×10^5MT
	population variance(σ^2_y)	7.5758×10^7MT^2
UC*	population mean($\overline{Z}$)	6.122217×10^5MT
	population variance(σ^2_z)	6.9741×10^7MT^2

(1) * population size, N=100
(2) Actual CO_2 emissions for the week of July 1987: 6.124×10^5MT [25]

Step 4: Find variance decreasing rate VDR_L by Eq.(6)

Step 5: If $VDR_L<VDR_{L-1}$, let $L=L+1$ and go to step 3; otherwise, let $L=L-1$ and go to step 6.

Step 6: Find the total sample size (n) at specified minimum variance by Eq.(10).

Step 7: Find sample sizes (n_k) in individual strata by Eq.(11).

Step 8: Draw a simple random sample in each stratum.

5.4 Unit Commitment, Including Economic Dispatch

For each of the n simple random sample combinations obtained in section 5.3, calculate CO_2 emission pollutants of generation system by the conventional unit commitment, including economic dispatch and yield n CO_2 emission pollutants values (z's).

5.5 Estimating the Mean Value of CO_2 Emissions

Find the estimate of population mean, $\bar{z}_{st}$, by Eq.(12).

6. NUMERICAL TESTS

6.1 System Description

The algorithm presented in section 5 has been tested on the Taipower generation system data of July 21–27, 1987. The generation system consists of 42 generating units. The system hourly load during the evaluation period is shown in Figure 1. Among the 42 units, six units are of nuclear type, which are located in the northern and southern regions. Eight of the 42 are hydroelectric units, located in the central region. The actual generation record of these nuclear and hydroelectric units with total generation in the range of 2177.9~4252.4 MW are used to shave the load. The hourly load after shaving is also depicted in Figure 1, which is to be met by the thermal units. For easier demonstration of the proposed algorithm, only the thermal generating outage combinations are evaluated. Their up/down statuses are evaluated by random number generators designed on the basis of the units' MTTF, and MTTR parameters shown in Table 12. The principal data characteristics of these thermal units for use in the unit commitment, including economic dispatch, are shown in Table 12.

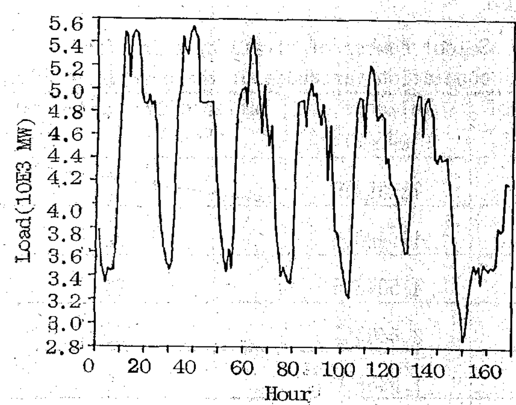

Figure 1 Load curve during 21–27 July, 1987

6.2 CO_2 Emission Pollutants Evaluation

The algorithm in section 5 was applied to estimate the CO_2 emission pollutants of the evaluation period. The computation results are summarized below:

Stage 1: Monte Carlo simulation of units' outage combinations (with population size N=100).
Stage 2: Approximate generation scheduling — The selected 100 CO_2 emission pollutants values are summarized in Table 6.
Stage 3: Stratified sampling — The step–by–step results are given in Tables 7 ~ 10. As shown, the selected number of strata (L) is 6, and sample size (n) is 10.
Stage 4: Conventional unit commitment including economic dispatch.
Stage 5: Population mean estimation — Refer to Table 10, the estimated mean ($\bar{z}_{st}$) is 6.115807×10⁵ MT. Take the population mean (6.122217×10⁵ MT) in Table 11 as reference, the estimation error is 0.105%.

With stratified sampling, the estimation variance decreases from the original population variance (6.9741×10^7 MT^2) to

Table 7 The cum$\sqrt[3]{f}$ rule applied to the CO_2 emissions population

CO_2 emission $10^5\times$MT	Frequency f	$\sqrt[3]{f}$	cum$\sqrt[3]{f}$
5.764946~5.790980	1	1.0	1.0
5.790980~5.817010	1	1.0	2.0
5.817010~5.843040	3	1.44225	3.44225
5.846040~5.869070	3	1.44225	4.88445
5.869070~5.895100	2	1.25992	6.14442
5.895100~5.921130	6	1.81712	7.96154
5.921130~5.947160	5	1.70998	9.67152
5.947160~5.973190	7	1.91293	11.58445
5.973190~5.999220	14	2.41014	13.99459
5.999220~6.025250	13	2.35133	16.34592
6.025250~6.051280	8	2.0	18.34592
6.051280~6.077310	9	2.08008	20.42600
6.077310~6.103340	13	2.35133	22.77733
6.103340~6.129370	8	2.0	24.77733
6.129370~6.155410	7	1.91293	26.69026

Remarks : (a) Unit of measurement : Metric ton(MT)
(b) CO_2 released due to fuel consumption : 0.3825 MT/Gcal for coal and 0.3149 MT/Gcal for oil
(c) CPU time:0.01sec (on SUN 4/60 Workstation)

Table 8 Stratum boundaries evaluated for the CO_2 emissions population

Stratum code , k	Interval , $10^5\times$MT	Variance(σ^2_k) , ($10^6\times MT^2$)	Frequence , N_k
1	5.764946~5.843040	10.2152	5
2	5.843040~5.921130	5.1219	11
3	5.921130~5.973190	3.6057	12
4	5.973190~6.025250	2.3829	27
5	6.025250~6.077310	2.9161	17
6	6.077310~6.155410	4.8620	28

4.0073×10^5 MWh^2. Referring to Table 11, the computing time required by Monte Carlo is mainly spent on the unit commitment process applied to n sample states rather than on the formulation of populations S and Y (ref. Table 7).

In the study, the actual values for the week of July 1987 [25] (see Table 6) was used as the reference to compare the accuracy of our proposed Monte Carlo simulation algorithm. Figure 2 depicts the errors of CO_2 emissions evaluated by our proposed Monte Carlo simulation algorithm. The simulation error of LDC approach is resulted mainly from its representation of load and generation scheduling model. The degree of error is system dependent. In contrast, the unit commitment and the availability state population with an extremely large size can simulate the actual system operation. But in the practical implementation, sampling introduces simulation error and the degree of error is sample dependent. Referring to section 3, our proposed Monte Carlo simulation algorithm allows the pre–specification of simulation precision by setting V of Eq.(10).

Table 9 Select number of strata by stratifid population variances

Number of strata(L)	Variance ($10^6\times MT^2$)	Variance decreasing rate (VDR_L)
1	75.75805	
2	16.50180	4.590896
3	4.02139	4.103506
4	1.96600	2.045468
5	1.12486	1.747726
6	0.77900	1.444720
7	0.37500	2.077300

Table 10 Sample size allocation in CO_2 emissions estimation

Stratum code , k	Interval , $10^5\times$MT	Weight , (W_k)	Straum mean , ($\bar{y}_k$, 10^5MT)	Variance , (10^6MT^2)	Sample size , (n_k)
1	5.7649~5.8430	5/100	5.8117036	10.2152	1
2	5.8430~5.9211	11/100	5.8864172	5.1219	1
3	5.9211~5.9732	12/100	5.9497719	3.6057	1
4	5.9732~6.0253	27/100	5.9975843	2.3829	2
5	6.0253~6.0773	17/100	6.0518894	2.9161	2
6	6.0773~6.1554	28/100	6.1083335	4.8620	3

Table 11 Mean estimation for CO_2 emissions population

Strutum code , k	Sample size , (n_{ki})	Sample unit , (z_{ki})	Estimated stratum mean($\bar{z}_{sk}$, $10^5\times$MT)	Weight , (w_k)	Estimated population Mean ($\bar{z}_{st}$, $10^5\times$MT)	CPU Seconds*
1	1	5.91249	5.91249	1/6	6.115807	1800
2	1	5.97646	5.97646	1/6		
3	1	6.06079	6.06079	1/6		
4	2	6.09471 6.12581	6.11026	2/6		
5	2	6.16714 6.16949	6.16832	2/6		
6	3	6.19291 6.22247 6.23580	6.21706	3/6		

* on SUN 4/60 Workstation

7. CONCLUSIONS

This paper presents an algorithm to estimate the CO_2 emission pollutants of generation system during a pre-specified future period. Numerical test results of the algorithm in Taipower system were examined. Specific conclusions arising from this work can be summarized as follows:

(1) By Monte Carlo simulation, all the possible outage combinations of system generating units are well simulated. By the conventional unit commitment, including economic dispatch, the system's operating mechanism is well accounted.
(2) With the stratified sampling and population mean estimation techniques embedded, the estimation variance is reduced at a reasonably acceptable computation cost. Most importantly, the proposed stratification rule removes the judgmental input and renders the stratification process entirely mechanistic.
(3) The LDC approach over-estimates the production of base-load units, and under-estimates the peak-load production, resulting in an under-estimation of generation system CO_2 emissions.
(4) Based on the relative simulation accuracy and computing efficiency, for the long term production simulation, the LDC approach is preferred, but for the short term, the Monte Carlo is preferred.

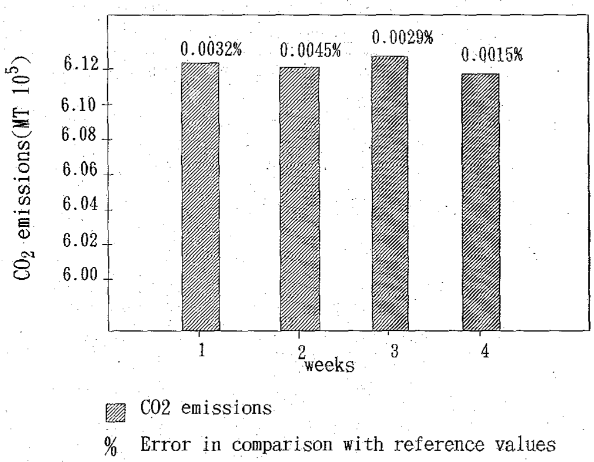

Fig.2 Results and error of CO_2 emissions evaluated by our proposed approach in July,1997(using actual values[25] as reference).

Application of our algorithm to Taipower's fuel budget is being conducted by the authors.

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Table 12 Characteristics of Taipower's thermal generation system in July 1987

Unit #	A_0 (Gcal/h)	A_1 (Gcal/MWh)	A_2 (Gcal/MW^{2}h)	A_3 (Gcal/MW^{3}h)	Pmin (MW)	Pmax (MW)	Fuel cost (US$/MWh)	Average full load cost (US$/MWh)	Minimum up time (hours)	Minimum down time (hours)	Start-up cost (NT$)	FOR	MTTF (hr.)	MTTR (hr.)	Fuel type
1	115.20	2.098	-0.1938E_3	0.5951E_6	220	500	6.6080	19.6702	8	14	5750	0.10	716	80	Coal
2	115.20	2.098	-0.1938E_3	0.5951E_6	220	500	8.6228	19.7039	8	14	5750	0.10	716	80	Coal
3	120.10	1.335	0.3834E_2	-0.4728E_5	135	300	8.4800	20.1090	8	15	8625	0.08	790	70	Coal
4	115.20	2.098	-0.1938E_3	0.5951E_6	242	550	8.6080	20.1736	8	14	5750	0.10	716	80	Coal
5	115.20	2.098	-0.1938E_3	0.5951E_6	242	550	8.6080	20.1736	8	14	5750	0.10	716	80	Coal
6	120.10	1.335	0.3834E_2	-0.4728E_5	135	300	6.5443	20.2614	8	15	8625	0.08	790	70	Coal
7	140.50	2.042	-0.1710E_3	0.5269E_6	80	200	12.0548	28.7088	7	10	1006	0.08	790	70	Coal
8	895.80	2.110	0.5000E_5	0.2100E_6	65	140	12.1050	28.7993	7	10	4312	0.06	2716	144	Coal
9	67.22	2.209	0.4500E_5	0.2500E_6	130	300	12.9900	29.4415	8	12	8625	0.08	790	70	Coal
10	52.17	2.208	-0.4253E_3	0.1728E_5	110	300	12.9900	30.6078	8	15	6325	0.08	790	70	Coal
11	99.65	2.085	-0.4272E_4	0.1429E_6	37	80	12.1265	30.6353	7	10	4025	0.06	2716	144	Coal
12	31.83	2.254	-0.3077E_2	0.1844E_6	68	140	15.3715	36.2285	8	15	2875	0.06	2716	144	Coal
13	99.65	2.085	-0.4272E_4	0.1429E_6	125	500	17.5288	37.3953	7	7	2875	0.07	1002	75	Oil
14	140.50	2.042	-0.1710E_3	0.5269E_6	125	500	17.5288	38.7068	7	7	2875	0.07	1002	75	Oil
15	80.10	1.510	0.8100E_3	-0.6601E_6	100	580	17.5288	39.0448	7	5	575	0.05	972	49	Com
16	89.58	2.110	0.5000E_5	0.2100E_6	125	500	17.5288	39.3008	7	7	2875	0.07	1002	75	Oil
17	120.00	2.135	0.4000E_5	0.2500E_6	125	500	17.5413	40.1778	8	12	8625	0.07	1002	75	Oil
18	76.41	2.211	0.4500E_5	0.2500E_6	94	375	17.5413	40.3355	8	12	13937	0.05	972	49	Oil
19	76.41	2.211	0.4500E_5	0.2500E_6	94	375	17.5413	40.3355	8	12	8625	0.05	972	49	Oil
20	72.44	2.150	-0.1710E_3	0.5269E_6	125	500	17.5413	40.6000	7	7	2875	0.07	1002	75	Oil
21	16.16	2.616	-0.1412E_1	0.2849E_3	26	42	15.5275	43.0000	7	15	1150	0.06	2716	144	Coal
22	18.08	2.594	-0.1758E_1	0.3547E_3	24	42	15.5275	43.0968	8	10	1150	0.06	2716	144	Coal
23	38.24	1.760	0.2997E_2	-0.1821E_5	1	118	35.0250	81.7815	0	0	575	0.07	1002	75	G.T
24	38.24	1.760	0.2997E_2	-0.1821E_5	1	118	34.4750	82.8323	0	1	575	0.07	1002	75	G.T
25	38.24	1.760	0.2997E_2	-0.1821E_5	1	118	34.9750	84.0408	0	0	575	0.07	1002	75	G.T
26	38.24	1.76	0.2997E_2	-0.1821E_5	1	248	34.6750	97.9813	0	1	575	0.08	790	70	G.T
27	38.24	1.765	0.2997E_2	-0.1821E_5	1	280	34.3250	100.4098	0	1	575	0.07	1002	75	G.T
28	38.24	1.76	0.2997E_2	-0.1821E_5	1	390	34.2500	109.2865	0	1	575	0.05	972	49	G.T

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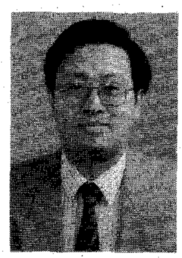
9. BIOGRAPHIES



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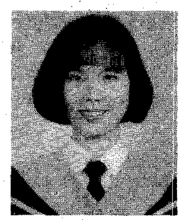

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