Soft-Error-Rate Adaptive Intervals for Low-Overhead Checkpoint Mechanism

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Abstract: Soft errors are increasingly important threats to the reliability of integrated circuits. Chips manufactured in advanced technologies show variations in *SER* caused by variations in the process parameters. Ongoing reduction of feature sizes and complexity of operating environment (temperature, voltage, radiation pressure and so on), *SER* variation is increasingly manifesting. Checkpoint is one of the most popular recovery method used for many systems, and the intervals of checkpoint can obviously influence performance. However, optimal intervals of checkpoint rely on *SER*. Theoretically speaking, *SER* adaptive checkpoint (SACP) which dynamically match checkpoint intervals with real time *SER* can improve checkpoint overhead under variable *SER*. But benefits of SACP are relative with *SER* variation. We give a mathematical model of *SER* variation and proposal a way to predict *SER* based errors occurred most currently. Results show high accuracy of *SER* prediction and much overhead improvement of SACP.

Key words: Soft-error-rate, adaptive, error variation, checkpoint intervals.

1. Introduction

Soft errors including SBU (single-bit-upset) and MBU (multiple-bit upset) are increasingly important threats to the reliability of integrated circuits fabricated in advanced CMOS technologies. Researchers expect an aggregate effect on soft-error rate (*SER*) of a chip. The error rate at 16-nm may be almost 100 times that at 180 nm [1]. Ongoing reduction of feature sizes has increased the probability that a single particle causes an MCU (Multiple-cell upset). It has been observed that a single neutron caused more than 50 bit flips in an SRAM of 65nm [2]. During neutron-accelerated *SER* tests of SRAMs in advanced processes, it is not unusual to observe that more than 50% of the upset events are MCUs [2], implying ECC techniques generally applied are more and more not capable of protecting systems.

Chips manufactured in advanced technologies gradually show variability on *SER* caused by variation in the process parameters. Voltage supply variability, voltage threshold variability and channel length variability at the lower level are directly associated with overall circuits at the higher level, not only performance variability and power variability, but also *SER* variability. Process variability causes that the *SER* vulnerability of an SRAM bit cell is not the same for its two data states. Experimental results for a 90-nm embedded SRAM showed that the differences can be almost a factor of 4 [3]. SRAM bit cells are symmetric by design, however sequential logic are not. As a result, the *SER* of sequential logic usually varies with the data state (0/1) and clock state (HIGH/LOW), the differences can be nearly 10X [4]. *SER* differences caused by process variability while chips manufactured and designed will eventually show *SER*

variations while systems running, meaning *SER* of systems may not keep constant but change from time to time.

Moreover, *SER* is highly associated with operating environment (temperature, voltage, radiation pressure and so on), which is not constant always but variable sometime. As computing is emerging anywhere and any-time, operating environment of many systems are variable, such as spacecraft, smart city system, unmanned verticraft, intelligent vehicle. As cars drive from New York City to Denver, CO, USA, *SER* increase 3.5X (due to altitude increased by 1.6KM) [5]. Many systems employ dynamic mechanisms to decrease power or energy, like DVFS, which also making voltage or frequency variable. Ongoing reduction of feature sizes and complexity of operating environment, *SER* variation is increasingly manifesting.

One of the most popular recovery methods is checkpoint. During checkpointing shown in Fig. 1, application entire statement is written to storage so that in occurrence of errors application can resume its work from the last checkpoint rather than from the beginning. T_{ex} in Fig. 1 is execution time of application, T_{ov} is time to store application statement, T_r is time to recovery application, T_{solve} is solve time for application which is equal to $N \times T_{ex}$, N is the number of passed segments required to complete a calculation. Intervals of checkpoint T_{ex} can obviously influence checkpoint performance.

Based on checkpoint model proposed by Daly [6], Fig. 2 shows how the performance overhead varies with checkpoint intervals, $overhead = (T_{total} - T_{solve}) / T_{solve}$. Optimal checkpoint interval for MTTE (mean time to errors) = 100min is 21min. Keeping the interval while *SER* changing to MTTE = 10min or MTTE=1000min, overhead will be 550% or 12%. However, overhead at optimal interval is 235% or 7%. So *SER* adaptive intervals of checkpoint can reduce overhead for variable *SER*. Theoretically speaking, *SER* adaptive checkpoint (SACP) which dynamically matches checkpoint intervals with real time *SER* can improve checkpoint overhead under variable *SER*.

Fig. 1. checkpoint model.

Fig. 2. Checkpoint overhead.

There are two points to reduce overhead for present checkpoint mechanism: reducing MTTE or time overhead to update checkpoint. Differently, the view of *SER* adaptive checkpoint (SACP) is that analyze occurrence of errors more carefully and match checkpoint interval with real time *SER* dynamically. Benefit of SACP is relative with *SER* variation (how large the variation takes and how long it keeps), so we firstly have to evaluate impact of *SER* variability on *SER* adaptive checkpoint.

We make the following contribution in this paper: 1. Based on how *SER* affected by temperature, voltage, radiation pressure and so on, we give a mathematical model with four parameters to quantized *SER* variation. 2. We study impact of variable *SER* on overhead of present checkpoint and *SER* adaptive checkpoint, indicating optimal benefits of SACP. 3. We proposal a way to predict *SER* based dynamic prediction window, showing practical benefits of SACP.

2. Background and Related Works

This paper focus on decreasing checkpoint overhead under variable *SER*. *SER* can be described by mean time to errors(MTTE) or number of errors occurred in unit time, and this paper will use later, that is $SER=1/MTTE$.

SER variation. Soft errors are caused by either neutrons generated by cosmic radiation interacting with the earth's atmosphere or alpha particles emitted by radioactive impurities that are present in chips and package materials. *SER* can be get from the following equation [7]:

$$SER = \text{Constant} \times \text{Flux} \times \text{Area} \times e^{-Q_{\text{crit}}/Q_{\text{coll}}}$$

Flux is the alpha or neutron flux experienced by the circuit, Area is the effective diffusion area, Q_{crit} is Critical charge, and Q_{coll} is the collection efficiency. Flux varies with altitude, location on the earth, concrete thickness of building, solar activity and so on. Q_{crit} depends on the supply voltage and temperature. Table 1 lists variable factors related to *SER*.

Table 1. Variable Factors Related to *SER*

variable factor X	how <i>SER</i> varies with X	amplitude of <i>SER</i> variation*
Altitude	$SER_0 \times e^{0.9x-0.03x^2}$ [5]	over 100 (sea level to flight level 12KM)
Latitude		3 (20N–60N)
Concrete Thickness	$SER_0 \times e^{-2.7x}$ [8]	15 (0–1m)
Solar Cycle		1.3 [8](day to next day) 1.6 [8](month to next month)
Voltage	$SER_0 \times e^{-1.3x+0.3}$ [9]	3 (0.4V~1.0V)@45nm
Temperature	$\approx \exp[10]$	3 (25C -110C)

* defined as maximal *SER* divided by minimum *SER*.

Form Table 1, we can see *SER* exponentially varies with most variable factor, for variable factor $X \in \{\text{Altitude, Thickness, Voltage, Temperature}\}$, *SER* could be

$$SER(X) = SER_0 \times e^{C_x \cdot (X - X_0)} \quad (1)$$

X_0 and SER_0 are a pair known value of X and corresponding *SER*, C_x is a constant indicating amplitude of *SER* variation with X variation per unit. Take altitude for example, $C_x=0.8$, meaning *SER* will increase $e^{0.8}$ per kilo-meter higher. If $C_x < 0$, indicating a decrease of *SER* while X increase, such as voltage and thickness.

In summary, amplitude of *SER* variation caused by operating environment can be from several to a hundred and caused by process variability can be ten. Considering both, amplitude of *SER* variation can be nearly thousand.

Checkpoint. Checkpoint technique is commonly used to recover from application failure. One aspect of employing checkpoint is properly assigning checkpoint intervals T_{ex} . Daly[6] proposal a accurate ways based *SER* and T_{ov} to determine the optimum checkpoint interval. We also use Daly's method to determine checkpoint intervals in this paper.

Adaptive checkpoint. Previous research improving overhead focused primarily on decreasing the checkpoint time of data transferred [11], [12], while relying on constant checkpoint frequency. Gerofi [13] proposal an algorithm that adapts dynamically to the properties of the workload being executed, such as changes in the number of dirtied memory pages, network and disk I/O operations, as well as to the network bandwidth available for replication. The results show benefits of adaptive checkpoint. The most difference with previous works is that we are focusing on *SER* variation which has rarely been studied.

3. Modeling SER Variation

We define SER at time t as $SER(t)$, let initial SER be SER_0 , so constant SER is $SER_c(t) = SER(0) = SER_0$. Variable SER according to Eq. (1) is

$$SER_v(t) = SER_0 \times e^{Cx \times (X(t) - X_0)} \quad (2)$$

$X(t)$ usually relevant to system type, application field, operating environment and so on. Variation of $X(t)$ based X_0 is shown as Eq.(3)

$$X(t) = \begin{cases} X_0 & t \% T \leq T - T_v \\ X_0 + a \times \sin(\pi(t - T + T_v) / T_v) & t \% T > T - T_v \end{cases} \quad (3)$$

With a indicating the largest amplitude increased or decreased, T is cycle time of variation and we use the mod “%” operator to make it, T_v is time for variation amplitude a (shown in Eq.(3)) sustained. Here we use $\sin()$ function to describe variation for a complicated variation can be regarded as some simultaneous simple $\sin()$ variation. Fig. 3 gives the $X(t)$ as $a=-0.5$ and $a=1$. Take $X(t)$ to Eq.(2), we have

$$SER_v(t) = \begin{cases} SER_0 & t \% T \leq T - T_v \\ SER_0 e^{A \times \sin(\pi(t - T + T_v) / T_v)} & t \% T > T - T_v \end{cases} \quad (4)$$

Here we make $A = Cx \times a$, Cx is SER variation per unit $X(t)$ variation, a is $X(t)$ total variation, so A is SER total variation for $X(t)$. Take altitude as an example, $Cx = 0.8$ (SER increased with $e^{0.8}$ time per kilo-meter increased), suppose $a = 5$ KM, so $A = 4$, meaning SER increased to e^4 time while $X(t)$ increased. Fig. 4 gives $SER_v(t)$ examples for $A = -1$, $A = 0.5$ and $A = 3$.

We can get number of errors occurred one cycle T by cumulative $SER_v(t)$ from 0 to T , and we can see number of errors at $A = 3$ is greater than $A = 0$, and that at $A = 0$ is also greater than $A = -1$. Overhead is greatly relative with errors number, and this paper is going to study overhead due to SER variability, so we use a factor K to equalize errors of $SER_v(t)$ in Eq.(5).

$$SER_v(t) = \begin{cases} SER_0 \times K & t \% T \leq T - T_v \\ SER_0 \times K e^{A \times \sin(\pi(t - T + T_v) / T_v)} & t \% T > T - T_v \end{cases} \quad (5)$$

Fig. 3. Examples of $X(t)$ variation.

 Fig. 4. $SER(t)$ variation.

 Fig. 5. $SER(t)$ variation equalized.

Number of errors in every T for constant SER is $\int_0^T SERc(t)dt = SER0 \times T$. We equalize errors for $SERv(t)$ as following function $\int_0^T SERv(t)dt \times K = SER0 \times T$, so $K = SER0 \times T / \int_0^T SERv(t)dt$ and value of K is determined by A and T_v/T . Fig. 5 shows the $SERv(t)$ equalized.

SER variation we studied in this paper is based on Eq.(5), we summery the parameters as following:

- $SER0$: the average SER in every cycle T .
- A : amplitude of SER variation, defined as maximal SER /minimum $SER = e^{|A|}$. We categorize SER variation as increased variation if $A > 0$ and decreased variation if $A < 0$.
- T_v : T_v is duration for variation sustained.
- pn : $pn = T_v/T$ is time proportion of variation, T is cycle time of variation.

Our goal is to study how the parameters ($SER0$, A , T_v , pn) impact checkpoint overhead for increased and decreased variation respectively. SER variation actually is more complicated than we modeled in Eq.(5), however, we can regard a complicated variation as some simultaneous simple variation.

4. SER Prediction

SER is usually calculated by number of errors occurred/time systems have run. Due to variation, we could not use errors occurred long time ago to predict real-time SER , just as Fig. 6(a) shown. Simulated results in Fig. 6(a) manifest delay between theoretical SER and predicted SER using errors occurred in 200 hours. So the key to SER prediction is proper time of errors occurred, and we define periods employed to predict SER as prediction window (PW).

Fig. 6. *SER* prediction; (a) Prediction window=200h, deviation cause by delay; (b) Prediction window=10h, deviation cause by random. (Red line is theoretical *SER* as Eq.(5), black points are simulated errors occurrence based red line, green points are *SER* we predicted based black points. Suppose $SER_0=1/100\text{min}^{-1}$).

Tow reason decreasing accuracy of *SER* prediction is random of errors occurred and delay due to *SER* variation. Errors occurred randomly (as Fig. 6(b)) and we need many errors to amortize deviation of *SER*. Whereas we should use errors occurred as current as possible for less delay deviation. Unfortunately, the two ways to decrease deviation is usually contrary. More errors to amortize random deviation indicate longer time ago errors to be used, which will obviously worsen prediction accuracy under low *SER*.

To balance the deviation cause by delay and random, we employ shorter PW when *SER* is largely changing and longer PW when *SER* relative constant, as shown in Table 2.

Table 2. Algorithm of Dynamic Prediction Window (DPW)

Functions: numbErr(pw): number of errors occurred during prediction window; $SER(pw)$: <i>SER</i> calculated by numbErr(pw)/pw; RE(s1,s2): relative error of s1 and s2	
input: t: current system time; Nt: number of errors occurred at current time; Time[Nt]: time the ith error occurred, used for numbErr(pw)	
output: $SER(t)$	
1...MTTE=t/Nt; pw =10×MTTE 2...WHILE numbErr(pw)>50 3... pw = pw - MTTE; //reduce pw 4...IF pw<10×MTTE 5... RETURN $SER(pw)$; //braek 6...s1= $SER(pw)$, s2= $SER(pw+MTTE)$; 7...WHILE RE(s1,s2)<1 and numbErr(pw)<50 8... pw = pw + MTTE; //increase pw 9... RETURN $SER(pw)$;	

DPW is dynamically increase or decrease the prediction window based RE(s1,s2) and numbErr(pw), making it works well for both continuous and variation. DPW is low-overhead and need no more system information, except the time of each error occurred.

We use error ratio between predicted *SER* and theoretical *SER* (shown as Eq.(5)) to measure precision of prediction, Error ratio of at t is defined as

$$ER(t) = \frac{\text{MAX}(SER_{pre}(t), SER_{OPT}(t))}{\text{MIN}(SER_{pre}(t), SER_{OPT}(t))}$$

We refer error ratio to overestimating if $SER_{pre}(t) > SER_{OPT}(t)$ or underestimating if

$SER_{pre}(t) < SER_{OPT}(t)$. Sum of ER as entire application ran is

$$ER = \sum_{i=1}^N \left(ER(t_i) \times \frac{T_{ex_i}}{T_{solve}} \right) \quad (7)$$

Here N is number of checkpoint intervals, t_i is the time i th interval started, $T_{ex}(i)$ is length of i th interval, T_{solve} is sum of T_{ex} . Sum of ER is great than 1, the larger means the worse precision of prediction.

5. Simulation Methods

We simulate the checkpoint mechanism as following steps in Table 3. The simulation generates pseudo-random errors in a Poisson distribution.

Based on [6], [14], basic parameters for checkpoint are given: $SER0=1/100\text{min}^{-1}$, $T_{total}=3200\text{h}$, time overhead to update checkpoint is 2min, time to recovery errors is 4min. T and T_v are relative to $SER0$ (enough errors should occur to show SER variation in every T), here we suppose $T=800\text{h}$, $T_v=400\text{h}$.

Table 3. Method to Simulate Checkpoint

Functions	
T_{ex} :	checkpoint intervals; comput $T_{ex}(ser)$:calculate T_{ex} based SER ;
$RE(s1,s2)$:	relative error of $s1$ and $s2$, equal to $\text{abs}(s2-s1)/s1$.
Parameter: T_{total} : total simulated time	
step: minimum time unit for simulation	
Time[Nt]: time the i th error occurred, used for numbErr(pw)	
output: T_{solve} . so overhead= $(T_{total} - T_{solve})/T_{solve}$	
1...WHILE	timeSIM< T_{total}
2...	timeSIM = timeSIM + step
3...	IF error occurred in this step
4...	Rflag = 1 // start to recovery
5...	ELSE IF Rflag==1 and recovery finished
6...	T_{ex} = comput $T_{ex}(ser)$; Rflag==0
7...	ELSE IF checkpoint interval is finished
8...	$T_{solve} = T_{solve} + T_{ex}$, T_{ex} = comput $T_{ex}(ser)$;

5.1. Determining Simulation Parameters

Parameters we need to determine is: how less should simulation step be (which will determine the simulation precision) and how many times should the simulation need to repeat for each case (which will average the simulation deviation).

The step of simulation has great influence on result precision. For Poisson distribution simulated, only one error occurred per simulation step at most, so relative error of number occurrence is $(\lambda \times \text{step} - 1 \times (\lambda \times \text{step})e^{-\lambda \times \text{step}})/(\lambda \times \text{step}) = 1 - e^{-\lambda \times \text{step}}$. Given $\lambda = SER0 = 1/100\text{min}^{-1}$, when step=1min, 0.1min, 0.01min, relative error is respectively 0.99%, 0.10%, 0.01%, so we donate step=0.1min to expect relative error of number occurrence less than 0.1%.

How many times we should simulated per case to average simulation result? According to [15], we denote 99% confidence level, 0.1% relative error, and get times>3458. We simulated 3500 times per case, so we can assure a 0.1% precision for errors simulated.

5.2. Analysing and Optimizing Simulation Error

The values we concerned with are number of errors really occurred and overhead of checkpoint, and we analyzing simulation error by comparing the true value with outcome of simulation, which is listing in Table 4. From basic parameters for checkpoint, true value of errors number is $3200 \times 60/100 = 1920$. We calculate true value of overhead by model given by Daly [6].

Table 4. Errors Simulated Precision for Different Amplitude A

method	Number of errors				Overhead (%) and relative error(%)			
	$A=0$	$A=1$	$A=3$	$A=5$	$A=0$	$A=1$	$A=3$	$A=5$
true value	1920	1920	1920	1920	28.00	27.76	27.06	26.89
simulated step=0.1min	1918.73	1917.74	1911.71	1906.56	28.17 (0.61)	27.62 (0.50)	26.58 (1.77)	26.39 (1.85)
simulated step=MIN{0.1, $0.1 \times SER_0 / SER_v(t)$ }	1918.21	1918.97	1918.10	1918.54	28.17 (0.61)	27.82 (0.22)	27.24 (0.67)	27.06 (0.63)

Table 4 shows that for $A=0$ simulation with 0.1min step fits well for both errors number (relative error is 0.07%) and overhead (relative error is 0.61%). However, SER variation will affect the precision. Error number not good for $A=5$ (relative error 0.7%), in which errors may occur much more in short time. We used a viable step for high SER to optimizing simulation error, as step is minimum of 0.1 and $0.1 \times SER_0 / SER_v(t)$. The viable step fit very well for all value of A , making relative error of errors number less than 0.1% and overhead less than 1.0%.

We simulated respectively for the following methods:

- FIX, fixed interval of checkpoint, the intervals are computed with the SER_0 and never change during system execution.
- SACP_OPT, SER adaptive intervals with the theoretical SER as Eq.(5), we use SACP_OPT to evaluate the optimal benefit of SACP.
- SACP_DPW, SER adaptive interval with SER predicted by DPW, in order to show the benefit can be achieved by SACP.

6. Results

In order to clearly describe overhead, we make the agreement with absolute improvement to be “overhead of FIX — overhead of SACP”, relative improvement to be “(overhead of FIX — overhead of SACP)/overhead of FIX” and improvement to be “relative improvement” if not specially speaking.

6.1. Average SER

Fig. 7 shows how overhead vary with SER_0 from $1/800\text{min}^{-1}$ to $1/12.5\text{min}^{-1}$. Results in Fig. 7(1) show that overhead benefit between SACP_OPT and FIX quickly increase from 1.3 % to 19%. Overhead improvement of SACP_OPT increase from 15% ($SER_0=1/100\text{min}^{-1}$) to 17% ($SER_0=1/12.5\text{min}^{-1}$). Results also show improvement nearly constant with SER less than $1/100\text{min}^{-1}$, that is to say SACP_OPT can always improve overhead by 15 % even for very low SER .

Fig. 7. Overhead and improvement for SER_0 with $|A|=3$.

Overhead improvement of SACP_DPW largely increases from 5% to 15% as SER_0 higher. SACP_DPW hardly improves overhead with SER less than $1/800\text{min}^{-1}$. because DPW predicts real-time SER based on errors, lower SER , less errors occurred at same periods, less precision for SER prediction.

We recall error ratio(ER) defined in Eq. (7) that ER of SACP_OPT is always 1 and more ER means more relative error of SER compared with SACP_OPT. Error ratio in Fig. 7(3) clearly shows that ER of SACP_DPW stays less than 2 with $SER_0 < 200\text{min}^{-1}$ and increases to 2.8 in $1/800\text{min}^{-1}$ and probably is greater than FIX with $SER_0 > 3200\text{min}^{-1}$ under which condition that so few errors occurred for SER prediction.

Fig. 7(2) and (4) show the same thing, summarily increased variations get better overhead improvement than decrease but worse error ratio of SER prediction.

6.2. Variation Amplitude A

Results in Fig. 8 show that as amplitude getting larger, overhead of SACP_OPT and SACP_DPW obviously decrease. When A less than 1, SACP_DPW is worse than FIX, while A larger than 2 SACP_DPW improve FIX overhead as much as by 25%. Results of error ratio show that DPW works well, especially for decreased variation with ER less than 2 for all A .

Fig. 8. Overhead and improvement for A with $SER_0 = 1/100\text{min}^{-1}$.

Overhead and corresponding improvement: overhead (bar shown with left axis) and corresponding improvement (line shown with right axis) for (1)overhead and corresponding improvement for increased variation (2)overhead and corresponding improvement for decreased variation (3)error ratio for increased variation (4)error ratio for decreased variation., with $|A|=3$, $SER_0=1/100\text{min}^{-1}$.

6.3. Variation Duration T_v

Results in Fig. 9 show nearly constant improvement of SACP_OPT, while improvement of SACP_DPW obviously decrease as $T_v < 200\text{h}$. If T_v is less than 25h, SACP_DPW will get no improvement. So few errors occurred in such a short periods make the variation maybe finished before SACP_DPW senses the variation.

6.4. Variation Proportion pn

Results in Fig. 10 show benefits increase as pn increase to 4/8, however, a more complicated trend after that for increased variation and decreased variation. The reasons are shown in Fig. 11.

Error ratio and overestimating error ratio shown in black and red bar are increase for both variations, however, proportion of overestimating error ratio decreases from 100% to 92% for increased variation but increases from 0% to 95% for decreased variation. Just as many research mentioned overestimating checkpoint interval will result in more overhead than underestimating, that is why overhead of increased

variation and decreased variation show differently trend in Fig. 10.

Fig. 9. Overhead and improvement for T_v with $pn=1/2$.

Fig. 10. Overhead and improvement for pn with $T_v=400h$.

Overhead and corresponding improvement: overhead (bar shown with left axis) and corresponding improvement (line shown with right axis) for (1)overhead and corresponding improvement for increased variation (2)overhead and corresponding improvement for decreased variation (3)error ratio for increased variation (4)error ratio for decreased variation., $T_v=400h$, $pn=1/2$.

Fig. 11. Error ratio of FIX for pn .

Error ratio (bar shown with left axis, sum of overestimating and underestimating error ratio labeled as ER_SUM and overestimating error ratio labelled as ER_OV) and overestimating proportion (line shown with right axis) for (a) increased variation (b) decreased variation}.

7. Conclusion

Soft errors are increasingly important threats to the reliability of integrated circuits. Chips manufactured in advanced technologies show variation in *SER* caused by variation in the process parameters. Ongoing reduction of feature sizes and complexity of operating environment, *SER* variation is increasingly manifesting. Checkpoint is the most popular recovery method, and the intervals of checkpoint can obviously influence performance. But optimal intervals of checkpoint are determined on *SER*. *SER* adaptive checkpoint which dynamically match checkpoint intervals with real time *SER* can improve checkpoint overhead under variable *SER*. But benefit of SACP is relative with *SER* variation, so in this paper we evaluate impact of *SER* variability on *SER* adaptive checkpoint.

This paper is focusing on *SER* variation which has rarely been studied. Based on how *SER* affected by temperature, voltage, radiation pressure and so on, we model *SER* variation with four parameters : average *SER* *SER*₀, variation amplitude *A*, variation duration *T_v* and variation proportion *pn*. With an exact simulation, we come out how much each parameter impacts the performance overhead of present checkpoint and *SER* adaptive checkpoint. We proposal a way to predict *SER* based dynamic prediction window (DPW), showing practical benefits of SACP. We categorize *SER* variation to increased variation and decreased variation. We give how much the parameters (*SER*₀, *A*, *T_v*, *pn*) impact checkpoint overhead for those four variability respectively.

Actual *SER* of systems may be more complicated than we modeled in this paper, however, we can regard a complicated variation as some simple variation acted simultaneously. Results in this paper can be referred to systems on weather *SER* variation need be considered or how much benefit *SER* adaptive checkpoint maybe achieved.

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