Stochastic formal correctness of numerical algorithms

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Abstract

We provide a framework to bound the probability that accumulated errors were never above a given threshold on numerical algorithms. Such algorithms are used for example in aircraft and nuclear power plants. This report contains simple formulas based on Lévy's and Markov's inequalities and it presents a formal theory of random variables with a special focus on producing concrete results. We selected four very common applications that fit in our framework and cover the common practices of systems that evolve for a long time. We compute the number of bits that remain continuously significant in the first two applications with a probability of failure around one out of a billion, where worst case analysis considers that no significant bit remains. We are using PVS as such formal tools force explicit statement of all hypotheses and prevent incorrect uses of theorems.

1 Introduction

Formal proof assistants are used in areas where errors can cause loss of life or significant financial damage, as well as in areas where common misunderstandings can falsify key assumptions. For this reason, formal proof assistants have been much used for floating point arithmetic [1, 2, 3, 4, 5] and probabilistic or randomized algorithms [6, 7]. Previous references link to a few projects using proof assistants such as ACL2 [8], HOL [9], Coq [10] and PVS [11].

All the above projects that deal with floating point arithmetic aim at containing worst case behavior. Recent work has shown that worst case analysis may be meaningless for systems that evolve for a long time, as encountered in industry. A good example is a process that adds numbers in ± 2 with a measure error of $\pm 2^{-24}$. If this process adds 2^{25} items, then the accumulated error is ± 2, and note that 10 hours of flight time at operating frequency of 1 kHz is approximately 2^{25} operations. Yet we easily agree that provided the individual errors are not correlated, the actual accumulated errors will continuously be much smaller than ± 2.

We present in Section 2 a few examples where this work can be applied. We focus on applications for *n counting in billions* and a probability of failure of about *one out of a billion*. Should one of these constraints be removed or lessened, the problems become much simpler. The main contributions of this work are the selection of a few theorems *amenable to formal methods* in a reasonable time, their application to *software and systems reliability*, and our work with PVS. Section 3 presents the formal background on probability with Markov's and Lévy's inequalities and how to use this theory to assert software and system reliability.

Doob-Kolmogorov's inequality was used in previous work [12]. It is an application of Doob's inequality, but it can be proved with elementary manipulations for second order moments. It is better than Lévy's inequality in the sense that it can applied to any sum of independent and centered variables. Yet it is limited by the fact that it bounds only second order moments.

2 Applications

Lévy's inequality works with independent symmetric random variables, as we safely assume in Sections 2.1 and 2.2. The applications presented in Section 2.3 cannot be treated by Lévy's inequality. Yet

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Listing 1: Accumulation of n values, which can also be viewed as a dot product with $d_i = b_i \times c_i$

```
1 a_0 = 0;
2 for (i = 1; i <= n; i = i + 1)
3   a_i = a_{i-1} ⊕ d_i; // is replaced by a_i = a_{i-1} + d_i + X_i
4     // to accommodate round-off errors and existing errors on d_i
```

we may obtain similar results with Doob's inequality which is not restricted to symmetric variables. Alas, we foresee that the time needed to develop Doob's inequality in any of the formal tools available today is at least a couple of years. Automatic treatment of all the following applications may use interval arithmetic that has been presented in previous publications and is now available in formal tools [4, 5].

2.1 Long accumulations and dot products

A floating point number represents $v = m \times 2^e$ where e is the exponent, an integer, and m is the mantissa [13]. IEEE 754 standard [14] on floating point arithmetic uses sign-magnitude notation for the mantissa and the first bit b_0 of the mantissa is implicit in most cases ($b_0 = 1$), leading to the first definition in equation (1). Some circuits such as the TMS320 [15] use two's complement notation for m, leading to the second definition in equation (1). The sign s and all the b_i are either 0 or 1.

$$v = (-1)^s \times b_0.b_1 \cdots b_{p-1} \times 2^e \qquad \text{or} \qquad v = (b_0.b_1 \cdots b_{p-1} - 2 \times s) \times 2^e \tag{1}$$

In fixed point notation e is a constant provided by the data type and b_0 cannot be forced to 1. We define for any representable number v, the *unit in the last place* (ulp) function below, with the notations of equation (1).

$$\mathrm{ulp}(v) = 2^{e-p+1}$$

The example given in Listing 1 sums n values, $(a_1, \ldots, a_n)$. When the accumulation is performed with floating point arithmetic, each iteration introduces a new round-off error X_i. One might assume that X_i follows a continuous or discrete uniform distribution on the range $\pm u$ with $u = \mathrm{ulp}(a_i)/2$, as trailing digits of numbers randomly chosen from a logarithmic distribution [16, pp. 254–264] are approximately uniformly distributed [17]. A significantly different distribution may mean that the round-off error contains more than trailing digits.

Errors created by operators are discrete and they are not necessarily distributed uniformly [18]. As they are symmetric, we only have to bound the moments involved in our main result, as in equation (2).

Mean	Variance	4th order moment	6th order moment	8th order moment
$\mathbb{E}(X_i) = 0,$	$\mathbb{E}\left(X_i^2\right) \leq \frac{u^2}{3},$	$\mathbb{E}\left(X_i^4\right) \leq \frac{u^4}{5},$	$\mathbb{E}\left(X_i^6\right) \leq \frac{u^6}{7},$	$\mathbb{E}\left(X_i^8\right) \leq \frac{u^8}{9}.$

(2)

If a_i uses a directed rounding mode, we introduce $X_i' = X_i - \mathbb{E}(X_i)$ and we use equation (2) again. We may also assume that d_i carries some earlier round-off errors. In this case, X_i is a linear combination of ℓ round-off errors satisfying equation (2) for a given u.

If d_i is a data obtained by an accurate sensor, we may assume that the difference between d_i and the actual value $\overline{d_i}$ follows a normal distribution very close to a uniform distribution on the range $\pm u$, with some new value of u. In this case, we model the error $d_i - \overline{d_i}$ by a symmetric random variable and X_i is the sum of two random variables ($\ell = 2$) satisfying equation (2) for a given u.

Table 1: Number of significant bits with a probability of failure $\mathbb{P}\left(\max_{1\le i\le n}(|S_i|)\ge\varepsilon\right)$ bounded by P

u	n	ℓ	P	$2k$	$\varepsilon\approx$	Number of significant bits
2^{-24}	10^9	2	10^{-9}	2	68.825	-6.10
				4	0.42832	1.22
				6	0.085786	3.54
				8	0.040042	4.64
				44	0.010153	6.62
2^{-24}	10^9	10	10^{-10}	2	486.66	-8.92
				4	1.7031	-0.77
				6	0.28156	1.82
				8	0.11939	3.06
				48	0.023873	5.38
u	$u^{-3/2}$	1	$u^{3/2}$	2	$\sqrt[4]{4u^{-2}/9}$	$(\log_2 u-1+\log_2 3)/2$
				4	$\sqrt[8]{4u^{-1}/9}$	$(\log_2 u-2+2\log_2 3)/8$
				6	$\sqrt[12]{100/81}$	$(2\log_2 3-\log_2 10)/6$
				8	$\sqrt[16]{4900u/729}$	$(-\log_2 u-2\log_2 70+6\log_2 3)/16$

After n iterations and assuming that all the errors introduced are independent, we want the probability that the accumulated errors have exceeded some user specified bound ε:

$$\mathbb{P}\left(\max_{1\le i\le n}(|S_i|)\ge\varepsilon\right)\le P \quad\text{with}\quad S_n=\sum_{i=1}^{n}X_i \quad\text{and}\quad \begin{array}{l}X_i \text{ is the sum of } \ell \text{ symmetric random}\\ \text{variables satisfying equation (2) for a}\\ \text{given } u.\end{array} \tag{3}$$

Previous work used Doob-Kolmogorov's inequality. We will see in Section 3 that we can exhibit tighter bounds using Lévy's inequality followed by Markov's one. Table 1 presents the number of significant bits of the results (i.e. $-\log_2\varepsilon$) for some values of u, n, ℓ, and P in equation (3). These values are obtained by using one single value of u, as large as needed. Tighter results can be obtained by using a specific value of u for each random variable and each iteration.

2.2 Recursive filters operating for a long time

Recursive filters are commonly used in digital signal processing and appear, for example, in the programs executed by Flight Control Primary Computers (FCPC) of aircraft. Finite impulse response (FIR) filters usually involve a few operations and can be treated by worst case error analysis. However, infinite impulse response (IIR) filters may slowly drift.

The theory of signal processing provides that it is sufficient to study second order IIR with coefficients b_1 and b_2 such that the polynomial $X^2-b_1X-b_2$ has no zero in $\mathbb{R}$. Listing 2 presents the pseudo-code of one such filter. A real implementation would involve temporary registers.

When implemented with fixed or floating point operations, each iteration introduces a compound error X_i that is a linear combination of ℓ individual errors satisfying equation (2) for a given u. As these filters are linear, we study the response to $d_0=1$ and $d_i=0$ otherwise, to deduce the accumulated effect

Listing 2: Infinite impulse response (IIR) filter operated on n iterations

```
y_{-1} = 0;  y_0 = d_0;
for (i = 1;  i <= n;  i = i + 1)
  y_i = d_i ⊖ b_1 y_{i-1} ⊖ b_2 y_{i-2};  // is replaced by y_i = d_i + X_i - b_1 y_{i-1} - b_2 y_{i-2}
    // to accommodate round-off errors and existing errors on d_i
```

of all the errors on the output of the filter. This response is defined as the sequence of real numbers such that

$$y_{-1} = 0, \qquad y_0 = 1, \quad \text{and} \quad y_n = -b_1 y_{n-1} - b_2 y_{n-2} \quad \text{for all} \quad n \geq 1.$$

This sequence can also be defined by the expression

$$y_n = b_2^{n/2} \sqrt{b_2 + 2b_1^2}\, \cos(\omega_0 + n\omega) \quad \text{with constants } \omega_0 \text{ and } \omega.$$

If the filter is bounded-input bounded-output (BIBO) stable, $0 < b2 < 1$ and the accumulated effect of the round-off errors is easily bounded by $\sqrt{b_2 + 2b_1^2} \;/\; (1 - \sqrt{b_2})$. Worst case error analysis is not possible on BIBO unstable systems. Our work and the example of Table 1 can be applied to such systems.

2.3 Long sums of squares and Taylor series expansion of programs

The previous programs introduce only first order effect of the round-off errors. We present here systems that involve higher order errors such as sum of square in Listing 3 that introduces D_i^2 and power series of all the random variables as in equation 4.

Assuming that d_i carries an error X_i in Listing 3, its contribution to the sum of square cannot be assumed to be symmetric. Lévy's inequality cannot be applied, but Doob's inequality provides a similar result, though a large number of foundational results are still lacking in existing formal libraries.

Listing 3: Sum of n squares

```
a_0 = 0;
for (i = 1;  i <= n;  i = i + 1)
  a_i = a_{i-1} ⊕ d_i ⊗ d_i;  // is replaced by a_i = a_{i-1} + X_i + (d_i + D_i)^2 = a_{i-1} + X_i + 2 d_i D_i + d_i^2 + D_i^2
    // to accommodate round-off errors and existing errors on d_i
```

The output of a system can always be seen as a function F of its input and its state $(d_1, \ldots, d_q)$. This point of view can be extended by considering that the output of the system is also a function of the various round-off errors $(X_1, \ldots, X_n)$ introduced at run-time. Provided this function can be differentiated sufficiently, Taylor series expansion at rank r provides that

$$\begin{aligned} F(d_1, \ldots, d_q, X_1, \ldots, X_n) &= F(d_1, \ldots, d_q, 0, \ldots, 0) \\ &+ \sum_{m=1}^{r} \frac{1}{m!} \left(\sum_{i=1}^{n} X_i \frac{\partial F}{\partial X_i} \right)^{[m]} (d_1, \ldots, d_q, 0, \ldots, 0) \\ &+ \left(\sum_{i=1}^{n} X_i \frac{\partial F}{\partial X_i} \right)^{[r+1]} (d_1, \ldots, d_q, \theta_1, \ldots, \theta_n), \end{aligned} \tag{4}$$

where θ_i is between 0 and X_i, and $(\cdot)^{[m]}$ is the symbolic power defined as

$$\left(\sum_{i=1}^{n} X_i \frac{\partial F}{\partial X_i}\right)^{[m]} = \sum_{1 \le i_1, \ldots, i_m \le n} X_{i_1} \cdots X_{i_m} \frac{\partial^m F}{\partial X_{i_1} \cdots \partial X_{i_m}}.$$

When the Taylor series is stopped after $m = 2$, we can use Doob's inequality to provide results similar to the ones presented in Table 1, provided the X_i are symmetric and independent. Higher order Taylor series don't necessarily create sub-martingales but weaker results can be obtained by combining inequalities on sub-martingales.

3 Formal background on probability

3.1 A generic and formal theory of probability

We rebuilt the previously published theory of probability spaces [12] as a theory of Lebesgue's integration recently became fully available. The new PVS development in Figure 1, still takes three parameters: $\mathtt{T}$, the sample space, $\mathscr{S}$, a σ-algebra of permitted events, and $\mathbb{P}$, a probability measure, which assigns to each permitted event in $\mathscr{S}$, a probability between 0 and 1. Properties of probability that are independent of the particular details of $\mathtt{T}$, $\mathscr{S}$, and $\mathbb{P}$ are then provided in this file.

A random variable X is a measurable application from $(\mathtt{T}, \mathscr{S})$ to any other measurable space $(\mathtt{T}', \mathscr{S}')$. In most theoretical developments of probability, $\mathtt{T}$, $\mathscr{S}$, and $\mathbb{P}$ remain generic, as computations are carried on $\mathtt{T}'$. Results on real random variables use $\mathtt{T}' = \mathbb{R}$ whereas results on random vectors use $\mathtt{T}' = \mathbb{R}^n$. Yet both theories refer explicitly to the Borel sets of $\mathtt{T}'$, the elements of the smallest σ-algebra containing the open sets of $\mathtt{T}'$.

As the Borel sets of $\mathbb{R}$ and $\mathbb{R}^n$ are difficult to grasp, most authors consider finite $\mathtt{T}$ and $\mathscr{S} = \mathscr{P}(\mathtt{T})$ for discrete random variables in introductory classes. This simpler analysis is meant only for educational purposes. Handling discrete and continuous random variables through different $\mathtt{T}$ and $\mathscr{S}$ parameters is not necessary and it is contrary to most uses of probability spaces in mathematics. Both discrete and continuous variables can be described on the same generic $\mathtt{T}$, $\mathscr{S}$, and $\mathbb{P}$ parameters in spite of their differences. Similarly, many authors work on sections $\{X \le x\}$ rather than using *the inverse images of Borel sets* of $\mathtt{T}'$ because the latter are difficult to visualize. Such a simplification is valid thanks to Dynkin's systems. But using abstract Borel sets rather than sections in formal methods often leads to easier proofs.

3.2 A concrete theory of expectation

The previous theory of random variables [12] made it possible to define them and to use and derive their properties. Very few results were enabling users to actually compute concrete results on random variables. Most of such results lie on a solid theory of the expected value. As most theorems in the latter theory are corollaries of a good theory of Lebesgue's integration, we have developed a formal measure theory based on Lebesgue's integration and we develop formal theorems on expected values, as needed in our applications.

The expected value is the (unique) linear and monotonous operator $\mathbb{E}$ on the set of $\mathbb{P}$-integrable random variables that satisfies Beppo-Lévy's property and such that $\mathbb{E}(\chi_A) = \mathbb{P}(A)$ for all $A \in \mathscr{S}$. We can also use the following definition when Lebesgue's integral exists:

$$\mathbb{E}(X) = \int_{\mathtt{T}} X \, \mathrm{d}\mathbb{P}.$$

Markov's inequality below is heavily used to obtain concrete properties on random variables.

```
probability_space[T:TYPE+,          (IMPORTING topology@subset_algebra_def[T])
                  S:sigma_algebra,   (IMPORTING probability_measure[T,S])
                  P:probability_measure]: THEORY
BEGIN
   IMPORTING topology@sigma_algebra[T,S],
             probability_measure[T,S],
             continuous_functions_aux[real],
             measure_theory@measure_space[T,S],
             measure_theory@measure_props[T,S,to_measure(P)]

   limit: MACRO [(convergence_sequences.convergent)->real]
                                                = convergence_sequences.limit
   h  : VAR borel_function
   A,B: VAR (S)
   x,y: VAR real
   n0z: VAR nzreal
   t:   VAR T
   n:   VAR nat
   X,Y: VAR random_variable
   XS:  VAR [nat->random_variable]

   null?(A)         :bool = P(A) = 0
   non_null?(A)     :bool = NOT null?(A)
   independent?(A,B):bool = P(intersection(A,B)) = P(A) * P(B)

   zero: random_variable = (LAMBDA t: 0)
   one:  random_variable = (LAMBDA t: 1)

   ; % Needed for syntax purposes!
   <=(X,x): (S) = {t | X(t) <= x}; % < = >= > /= omitted

   complement_eq: LEMMA complement(X = x) = (X /= x) % More omitted

   ; % Needed for syntax purposes!
   +(X,x): random_variable = (LAMBDA t: X(t) + x); % More omitted

   borel_comp_rv_is_rv: JUDGEMENT o(h,X) HAS_TYPE random_variable
   partial_sum_is_random_variable:
     LEMMA random_variable?(LAMBDA t: sigma(0,n,LAMBDA n: XS(n)(t)))

   distribution_function?(F:[real->probability]):bool
                                     = EXISTS X: FORALL x: F(x) = P(X <= x)
   distribution_function: TYPE+ = (distribution_function?) CONTAINING
                                    (LAMBDA x: IF x < 0 THEN 0 ELSE 1 ENDIF)
   distribution_function(X)(x):probability = P(X <= x)

   convergence_in_distribution?(XS,X):bool
     = FORALL x: continuous(distribution_function(X),x) IMPLIES
                 convergence((LAMBDA n: distribution_function(XS(n))(x)),
                                         distribution_function(X)(x))

   invert_distribution:   LEMMA LET F = distribution_function(X) IN
                                P(x < X) = 1 - F(x)
   interval_distribution: LEMMA LET F = distribution_function(X) IN
                                x <= y IMPLIES
                                P(intersection(x < X, X <= y)) = F(y) - F(x)
   limit_distribution:    LEMMA LET F = distribution_function(X) IN
                                P(X = x) = F(x) - limit(LAMBDA n: F(x-1/(n+1)))

   F: VAR distribution_function
   distribution_0:                LEMMA convergence(F o (lambda (n:nat): -n),0)
   distribution_1:                LEMMA convergence(F,1)
   distribution_increasing:       LEMMA increasing?[real](F)
   distribution_right_continuous: LEMMA right_continuous(F)
END probability_space
```

Figure 1: Abbreviated probability space file in PVS

Theorem 1 (Markov's inequality)**.** *For any random variable X and any constant $\varepsilon > 0$,*

$$\mathbb{P}(|X| \geq \varepsilon) \leq \frac{\mathbb{E}(|X|)}{\varepsilon}.$$

Many theorems relate to independent random variables and their proofs are much easier once independence is well defined. The family $(X_1, \ldots, X_n)$ is independent if and only if, for any family of Borel sets $(B_1, \ldots, B_n)$,

$$\mathbb{P}\left(\bigcap_{i=1}^{n} (X_i \in B_i)\right) = \prod_{i=1}^{n} \mathbb{P}(X_i \in B_i).$$

The following characteristic property is used a lot on families of independent variables:
For any family of Borelean functions $(h_1, \ldots, h_n)$ such that the $h_i(X_i)$ are $\mathbb{P}$-integrable,

$$\mathbb{E}\left(\prod_{i=1}^{n} h_i(X_i)\right) = \prod_{i=1}^{n} \mathbb{E}(h_i(X_i)).$$

It is worth noting that the fact that n random variables are independent is not equivalent to the fact that any pair of variables is independent, and cannot be built recursively from $n-1$ independent random variables.

Future work may lead us to implement a theory of the law $\mathbb{P}_X$ associated to each random vector $X : \mathtt{T} \longrightarrow \mathbb{R}^n$, with a "transfer" theorem for any Borelean function $h : \mathbb{R}^n \longrightarrow \mathbb{R}$ below, and most properties of Lebesgue's integral including Fubini's theorem.

$$\mathbb{E}(h(X)) = \int_{\mathtt{T}} h(X)\, \mathrm{d}\mathbb{P} = \int_{\mathbb{R}^n} h\, \mathrm{d}\mathbb{P}_X$$

3.3 Almost certain a priori error bound

What we are actually interested in is whether a series of calculations might accumulate a sufficiently large error to become meaningless. In the language we have developed, we are computing the probability that a sequence of n calculations has failed because it has exceeded the ε error-bound somewhere.

Theorem 2 (Corollary of Lévy's inequality)**.** *Provided the (X_n) are independent and symmetric the following property holds for any constant ε.*

$$\mathbb{P}\left(\max_{1 \leq i \leq n} (|S_i|) \geq \varepsilon\right) \leq 2\,\mathbb{P}(|S_n| \geq \varepsilon)$$

Proof. We use a proof path similar to the one published in [19]. We define $S_n^{(j)}$ below with Dirichlet's operator δ_P, which is equal to 1 if the predicate holds and 0 otherwise. As the X_n are symmetric, the random variables S_n and $S_n^{(j)}$ share the same probability density function.

$$S_n^{(j)} = \sum_{i=1}^{n} (-1)^{\delta_{i>j}} X_i$$

We now define $N = \inf\{k \text{ such that } |S_k| \geq \varepsilon\}$ with the addition that $\inf \varnothing = +\infty$ and similarly $N^{(j)} = \inf\{k \text{ such that } |S_k^{(j)}| \geq \varepsilon\}$. Events $\max_{1 \leq i \leq n}(|S_i|) \geq \varepsilon$ and $N \leq n$ are identical. Furthermore,

$$\mathbb{P}(|S_n| \geq \varepsilon) = \sum_{j=1}^{n} \mathbb{P}(|S_n| \geq \varepsilon \cap N = j) = \sum_{j=1}^{n} \mathbb{P}\left(|S_n^{(j)}| \geq \varepsilon \cap N = j\right).$$

As soon as $j \leq n$, $2S_j = S_n + S_n^{(j)}$ and $2|S_j| = |S_n| + |S_n^{(j)}|$. Therefore, the event $\{|S_j| \geq \varepsilon\}$ is included in $\{|S_n| \geq \varepsilon\} \cup \{|S_n^{(j)}| \geq \varepsilon\}$ and

$$\mathbb{P}(N \leq n) = \sum_{j=1}^{n} \mathbb{P}(|S_j| \geq \varepsilon \cap N = j) \leq \sum_{j=1}^{n} \mathbb{P}(|S_n| \geq \varepsilon \cap N = j) + \sum_{j=1}^{n} \mathbb{P}\left(|S_n^{(j)}| \geq \varepsilon \cap N = j\right).$$

This ends the proof of Lévy's inequality. □

Should we need to provide some formula beyond the hypotheses of Lévy's inequality, we may have to prove Doob's original inequality for martingales and sub-martingales [20] in PVS. It follows a proof path very different from Doob-Kolmogorov's inequality but it is not limited to second order moment and it can be applied to any sub-martingale S_i^{2k} with $k \geq 1$ to lead to

$$\mathbb{P}\left(\max_{1 \leq i \leq n} (|S_i|) \geq \varepsilon\right) \leq \frac{\mathbb{E}\left(S_n^{2k}\right)}{\varepsilon^{2k}}.$$

Here, we use Markov's inequality applied to S_n^{2k} in order to obtain the results of Table 1:

$$\mathbb{P}(|S_n| \geq \varepsilon) = \mathbb{P}\left(S_n^{2k} \geq \varepsilon^{2k}\right) \leq \mathbb{E}\left(S_n^{2k}\right)/\varepsilon^{2k}.$$

Formulas

$$\begin{aligned}
\mathbb{E}(S_n^2) &= u^2\left(\tfrac{1}{3}n\right) \\
\mathbb{E}(S_n^4) &= u^4\left(\tfrac{1}{5}n + \tfrac{1}{3}n(n-1)\right) \\
\mathbb{E}(S_n^6) &= u^6\left(\tfrac{1}{7}n + n(n-1) + \tfrac{5}{9}n(n-1)(n-2)\right) \\
\mathbb{E}(S_n^8) &= u^8\left(\tfrac{1}{9}n + \tfrac{41}{15}n(n-1) + \tfrac{14}{3}n(n-1)(n-2) + \tfrac{35}{27}n(n-1)(n-2)(n-3)\right)
\end{aligned}$$

are based on the binomial formula for independent symmetric random variables

$$\mathbb{E}\left(S_n^{2k}\right) = \sum_{k_1+k_2+\cdots+k_n=k} (2k)! \frac{\mathbb{E}\left(X_1^{2k_1}\right)}{(2k_1)!} \frac{\mathbb{E}\left(X_2^{2k_2}\right)}{(2k_2)!} \cdots \frac{\mathbb{E}\left(X_n^{2k_n}\right)}{(2k_n)!}.$$

Proof. We first prove the formula below by induction on n for any exponent m.

$$\mathbb{E}\left(S_n^m\right) = \sum_{m_1+m_2+\cdots+m_n=m} m! \frac{\mathbb{E}\left(X_1^{m_1}\right)}{m_1!} \frac{\mathbb{E}\left(X_2^{m_2}\right)}{m_2!} \cdots \frac{\mathbb{E}\left(X_n^{m_n}\right)}{m_n!}$$

It holds for $n = 1$. We now write the following identity based on the facts that X_n are independent and symmetric. $\mathbb{E}\left(S_{n+1}^m\right) = \mathbb{E}\left((S_n + X_{n+1})^m\right)$ is also equal to

$$\mathbb{E}\left(\sum_{m_{n+1}=0}^{p} \frac{m!}{(m-m_{n+1})!m_{n+1}!} X_{n+1}^{m_{n+1}} S_n^{m-m_{n+1}}\right) = \sum_{m_{n+1}=0}^{p} \frac{m!}{(m-m_{n+1})!m_{n+1}!} \mathbb{E}\left(X_{n+1}^{m_{n+1}}\right) \mathbb{E}\left(S_n^{m-m_{n+1}}\right)$$

We use the induction hypothesis on $\mathbb{E}\left(S_n^{m-m_{n+1}}\right)$ and we collapse the summations. We end the proof for the even values of m after noticing that $\mathbb{E}\left(X_i^{2k+1}\right) = 0$ for any i and any k, since the X_n are symmetric. □

4 Perspectives and concluding remarks

To the best of our knowledge, this paper presents the first application of Lévy's inequality to software and system reliability of very long processes with an extremely low rate of failure. Our results allow any one to develop safe upper limits on the number of operations that a piece of numeric software should be permitted to undertake. In addition, we are finishing certification of our results with PVS. The major restriction lies in the fact that the slow process of proof checking has forced us to insist that individual errors are symmetric.

At the time we are submitting this work, the bottleneck is the full certification of more results using PVS proof assistant. Yet this step is compulsory to provide full certification to future industrial uses. We anticipate no problem as these results are gathered in textbooks in computer science and mathematics. This library and future work will be included into NASA Langley PVS library[1] as soon as it becomes stable.

The main contribution of this work is that we selected theorems that produce significant results for extremely low probabilities of failure of systems that run for a long time, and that are amenable to formal methods. During our work, we discarded many mathematical methods that would need too many operations or that would be too technical to be implemented with existing formal tools.

Notice that this work can be applied to any sequence of independent and symmetric random variables that satisfy equation (2). It is worth pointing out one more time that violating our assumption (independence of errors) would lead to worse results, so one should treat the limit we have deduced with caution, should this assumption not be met.

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