

# Reviews

## Applications of Reliable Scientific Computing

# Рефераты

## Приложения надежных научных вычислений

Allen, J. F., Kautz, H. A., Pelavin, R. N., and Tenenber, J. D. *Reasoning about plans*. Morgan Kaufmann, San Mateo, CA, 1991.

This collective monograph describes several versions of *interval temporal logic* (i.e., a logic in which knowledge about time is represented by using time intervals as a basic notion) and their use in actions planning.

M. Beltran

Little, Th. D. C. and Ghafoor, A. *Interval-based conceptual models for time-dependent multimedia data*. IEEE Transactions on Knowledge and Data Engineering 5 (4) (1993), pp. 551–563.

In scheduling multi-media presentations (i.e., in assigning time intervals to different events like showing a videoclip), one must take into consideration that some events must be scheduled during the others, some after the others, etc. To describe the ordering relation between time intervals corresponding to different events, the authors use Allen's interval algebra of ordering relations. In addition to ordering, we also know the *durations* of different events (sometimes, we only know the *intervals* of possible durations). The authors design an algorithm that checks whether given requirements on ordering and durations are consistent, and, if they are, produces a corresponding schedule.

D. E. Cooke

Pnueli, A. and Zuck, L. D. *Probabilistic verification*. Information and Computation 103 (1) (1993), pp. 1–29.

Probabilistic elements are often introduced in concurrent programs in order to solve problems that either cannot be solved efficiently or cannot be solved at all by deterministic programs. Interval-based temporal logic is often used to specify correctness conditions of concurrent programs. The paper presents a procedure that, given a probabilistic finite state program and a (restricted) temporal logic specification, decides whether the program satisfies its specification with probability 1.

From the authors' abstract

Levin, V. I. *Interval discrete programming*. Cybernetics and Systems Analysis 30 (6) (1994), pp. 866–874.

The ideal decision making situation is when we know what characteristic  $J$  we want to maximize, and we know the values  $J(a)$  of this characteristic for all alternatives  $a$ . In real life, even when we know  $J$ , we often do not know  $J(a)$  precisely; we only know the interval  $[J^-(a), J^+(a)]$  of possible values of  $J(a)$ . How do we then choose  $a$ ?

It is clear that if for some alternatives  $a$  and  $b$ , we have  $J^-(a) > J^+(b)$ , then  $b$  is worse than  $a$ , and thus,  $b$  will not be chosen. In many cases, however, after applying this "rule" we still have a lot of alternatives to choose from. For example, if we want to buy the most fuel efficient car, and the choice is between a car  $C_1$  with fuel consumption of 8–10 liters per 100 km and a car  $C_2$  with fuel consumption 9–12, then, according to the above criterion, both cars have to be considered. Common sense says that it is reasonable to choose the second car.

In general, if  $J^-(a) > J^-(b)$  and  $J^+(a) > J^+(b)$ , then we can prefer  $a$  to  $b$ .

The author applies this approach to 0–1 linear programming problems ( $\sum c_j x_j \rightarrow \max$  under the conditions  $\sum a_{ij} x_j \leq b_i$ ,  $x_j \in \{0, 1\}$ ), with interval bounds on the coefficients  $a_{ij}$ ,  $b_i$ , and  $c_j$ . Every problem of this type is reduced to two similar problems with real-valued coefficients.

V. Kreinovich

Pérez-González, F., Docampo, D., and Abdallah, C. *Bounding the frequency response for digital transfer functions: results and applications*. In: "Proc. of IEEE Digital Signal Processing Workshop", 1994, pp. 15–18.

A digital filter is a linear processing device that transforms the incoming signal  $x(n)$ ,  $n = \dots, 0, 1, 2, \dots$  into a filtered signal  $y(n)$  so that

$$y(n) - \sum a_k y(n-k) = \sum b_k x(n-k)$$

for some coefficients  $a_k$  and  $b_k$ . Digital filters can increase signal-to-noise ratio and compensate for the distortions imposed by the measuring device. An important characteristic of a filter is its (complex) frequency characteristic  $H(z) = H(\exp(i\omega))$  that describes how the filter transforms a sinusoidal periodic signal: if  $x(n) = x(\omega) \exp(i\omega n)$ , then  $y(n) = y(\omega) \exp(i\omega n)$ , where  $y(\omega) = H(\exp(i\omega))x(\omega)$ .

If we know the coefficients  $a_k$ ,  $b_k$  precisely, then, for every  $\omega$ , we can compute  $H(z)$  as  $H(z) = B(z)/A(z)$ , where  $B(z) = \sum b_k z^k$  and  $A(z) = 1 + \sum a_k z^k$ . In real life, we often know only the intervals  $a_k$  and  $b_k$  of possible values of the coefficients  $a_k$  and  $b_k$ ; in this case, we must describe the set of possible values of  $H(z)$ .

In principle, we can consider real and imaginary parts of  $H(z)$ , and apply interval computations to find a box that contains all possible values of  $H(z)$ . However, this box is an overestimation of the desired set (in the sense that not all values from the box are possible).

In the paper under review, the authors describe a simple (quadratic-time) algorithm that, given  $\omega$  and the intervals  $a_k$  and  $b_k$ , describes the exact polygons of possible values of  $A(z)$  and  $B(z)$ , and thus, enables us to describe the set of possible values of the ratio  $H(z) = A(z)/B(z)$ . As a result, the authors get exact bounds on the magnitude and phase of the frequency response  $H(z)$ .

S. Cabrera

Shaked, M. and Shanthukumar, J. G. *Stochastic orders and their applications*. Academic Press, San Diego, CA, 1994.

In many real-life problems, e.g., in economics, reliability theory, medicine, etc., we must choose between two alternatives whose consequences are not completely known. The book considers the case when we know the probabilities of different results; hence, each alternative is represented by a probability distribution on the set of possible results, i.e., as a random variable. How can we compare two random variables  $X$  and  $Y$ ? One possibility (called stochastic order) is as follows:

- In probability theory, a random variable  $X$  is usually defined as a probability measure on the set of all real numbers (that describes the probability of different values of this variable).
- The common-sense understanding of a random variable is better described by an alternative (equivalent) definition: a random variable is a mapping from a set  $\Omega$  with a probability measure  $\mu$  on it to the set of real numbers (for which  $x(\omega)$  has the desired probabilities).

We say that a random variable  $X$  is *smaller* than a random variable  $Y$  in the sense of stochastic ordering (and denote it by  $X \leq_{st} Y$ ) if there exists a set  $(\Omega, \mu)$  and two mappings  $x, y : \Omega \rightarrow R$  that represent, correspondingly, variables  $X$  and  $Y$ , and for which  $x(\omega) \leq y(\omega)$  for all  $\omega$ . The main result of stochastic ordering theory is a condition necessary and sufficient for  $X \leq_{st} Y$ : this condition is the inequality between distribution functions:  $P\{X \leq u\} \geq P\{Y \leq u\}$  for all real numbers  $u$ .

There also exist more complicated modifications of this definition.

The results presented in this book are based on the assumption that we know the probabilities; in many real-life situations, we do not know them. Many methods and ideas presented in the book can be naturally extended to this more general type of uncertainty.

For example, a similar choice problem occurs when we only know *intervals*  $\mathbf{X} = [x^-, x^+]$  and  $\mathbf{Y} = [y^-, y^+]$  of possible values of  $x$  and  $y$  that correspond to two alternatives. In this case, we can use the above-defined idea: Namely:

- Each interval  $\mathbf{X}$  can be represented as a mapping  $x : \Omega \rightarrow R$  from some set  $\Omega$  to the set of real numbers, for which the set of possible values of  $x(\omega)$  is exactly this interval  $\mathbf{X}$ .
- We can say that  $\mathbf{X}$  is *smaller* than  $\mathbf{Y}$  (and denote it by  $\mathbf{X} \leq_{st} \mathbf{Y}$ ) iff there exist two mappings  $x, y : \Omega \rightarrow R$  for which  $x$  represents  $\mathbf{X}$ ,  $y$  represents  $\mathbf{Y}$ , and  $x(\omega) \leq y(\omega)$  for all  $\omega \in \Omega$ .

A direct analogue of the main theorem mentioned above can be easily proven for intervals:

**Proposition 1.**  $[x^-, x^+] \leq_{st} [y^-, y^+]$  iff  $x^- \leq y^-$  and  $x^+ \leq y^+$ .

*Proof.* If  $x^- \leq y^-$  and  $x^+ \leq y^+$ , then we can take  $\Omega = [0, 1]$ ,  $x(\omega) = \omega \cdot x^+ + (1 - \omega) \cdot x^-$ , and  $y(\omega) = \omega \cdot y^+ + (1 - \omega) \cdot y^-$ .

Vice versa, if  $[x^-, x^+] \leq_{st} [y^-, y^+]$ , i.e., if there exists a joint representation  $x, y : \Omega \rightarrow R$ , then  $x^+ = x(\omega)$  for some  $\omega \in \Omega$ . For this  $\omega$ , we have  $x^+ = x(\omega) \leq y(\omega)$ ; but  $y(\omega) \leq y^+$ ; hence,  $x^+ \leq y^+$ . Similarly, there exists an  $\omega$  for which  $y^- = y(\omega)$ . For this  $\omega$ ,  $y^- = y(\omega) \geq x(\omega) \geq x^-$ .  $\square$

The book's theory is thus extendible to the case when we do not know probabilities at all. It is desirable to extend the book's results to the intermediate cases when we know *some* but not *all* probabilities, e.g., to the case when we know the *intervals* of possible values of probabilities.

In the majority of applications presented in the book, we do not really know all the probabilities, so, it looks like this generalization will be not technically difficult and very practically useful.

H. T. Nguyen and V. Kreinovich

Aalst van der, W. M. P. and Odijk, M. A. *Analysis of railway stations by means of interval timed coloured Petri nets*. Real-Time Systems 9 (1995), pp. 241–263.

Scheduling algorithms are usually based on the assumption that we know the exact durations  $d_i$  of all the tasks that we want to schedule. In real life, the durations  $d_i$  may vary. In rare cases when we know the probabilities of different durations, we can apply stochastic scheduling methods. Most often, however, we do not know the probabilities, we only know the upper bound  $d_i^+$  and the lower bound  $d_i^-$  for the duration  $d_i$ ; in other words, we know an *interval*  $[d_i^-, d_i^+]$  of possible values of duration  $d_i$ . In these situations, we want a schedule that satisfies the given constraints for all possible values of durations  $d_i$  from the given intervals. An algorithm for producing such a schedule is given in this paper. As an example, this algorithm is applied to a railway station.

V. Kreinovich