# Does Reduced Uncertainty Mean Greater Certainty?

## Project management with uncertain durations

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**Abstract**

*This paper explores how uncertainty in duration estimates is handled, with the subject area being new product development. In many projects simple deterministic estimates of nominal task duration may be sufficient (for several given reasons). Various methods for coping with uncertain durations are described, including PERT, fuzzy theory, and probabilistic computations (three sub-types). These are illustrated with representative data, and the benefits and disadvantages discussed. Two major risk areas with any and all stochastic estimating processes are identified as the unreliability of the estimates, and the ambiguous interpretation. Implications are:*

- *Project managers might benefit from greater familiarity with PERT.*
- *Software developers need to implement PERT better, and should also consider implementing fuzzy theory.*
- *Design managers might be best to aim for adequate rather than exhaustive project plans, scope definitions and risk assessments. They might complement this by active project monitoring to give flexible, fast, efficient and effective response during deployment.*

Keywords: duration, time, project management, design, uncertainty, PERT, fuzzy theory, Monte Carlo

## 1 Introduction

This paper explores the issues involved with managing uncertain time in engineering design projects. This is worth doing because time is a crucial factor for successful projects, especially as projects are by their very nature time-terminated.

Estimation and management of time is a key requirement for project success because time affects both schedule and cost. Time taken for tasks affects total project schedule directly, and indirectly affects project cost through wages. Therefore robust processes are required for managing time in projects.

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## 2 Case studies

***Organisation A***

This is a leading national research and development organisation. It focuses on applied research, particularly the application of science and engineering to solve real problems faced by industry. Its has a high dependency on external commercial income. Therefore it is necessary to satisfy external customers' expectations for (a) technical success, (b) a system delivered on time, and (c) cost containment.

| *Root causes* | *Risks (things that could go wrong)* |
|---|---|
| fixed price contracts (builds client confidence) | cost overrun |
| R&D projects with high novelty | technical risk |
| unique, one-off projects | no experience on which to base project plans, so fragile estimates of cost and duration |

*Summary: The high technical risk tend to result in schedule overruns and thus also cost excesses. Thus two main determinants of project success are accuracy of time estimates at planning, and management of time overruns during execution.*

**Organisation B**

This organisation designs and manufactures domestic appliances, particularly whiteware (stoves, ovens, cook-tops, dishwashers, cloths washers, dryers, fridges, freezers). This is a highly competitive market, where financial margins are slim. The organisation seeks to differentiate itself by innovative design. Products are refreshed every few years, by changing external appearances to align with latest home styling fashions, and making improvements to internal engineering components. However, these refresh projects have to be carefully managed.

| *Root causes* | *Risks (things that could go wrong)* |
|---|---|
| design changes to tooling are time consuming since the products have large sheet-metal or plastic injection molded parts | schedule overruns, pressure to meet market entry windows (e.g. Christmas sales period) |
| concurrent engineering approach: macroscopic design details are frozen early and released to initiate the downstream tool production | extra costs: if the frozen feature has to be modified after it has been embodied on the tool, then there are major additional costs, possibly even the scrapping of the tool. |
| | time overruns due to emerging problems in the concurrent schedule |

*Summary: Time estimates have to be initially accurate and closely monitored to ensure tight coordination during the concurrent processes.*

These case studies show the importance of time management during design. Also apparent are the difficulties introduced by high technical uncertainty and concurrent engineering.

## 3 Estimating task duration

There are various processes available to estimate task duration, depending on the desired level of treatment of uncertainty.

*Estimate nominal task durations*
The primary activity is to estimate nominal task durations. Typical inputs are estimates by workers or the project manager. The mechanism for making the estimates is predominately experience of the individual on related past projects. This of course is problematic when the new project is novel, since there is no experience on which to base estimates. But if experience is high then this is simple, quick, and reliable.

In most projects a simple *deterministic* estimate of nominal task duration is sufficient. Such an estimate carries no indication of uncertainty. To a large extent customers are content with this, for several reasons. First, many people can only deploy one solution strategy at a time, and therefore do not like indecision or ambiguity in the candidate solutions. Thus a deterministic estimate of project duration is just fine to many. Second, customers often commission a project specifically as a means to transfer the risks out of their own organisation. Thus a deterministic estimate of duration might sometimes be received by the client as a message of reassurance about the competency of the project organisation.

***Exercise 1: What is the diameter of the Earth? Estimate it quickly without thinking about it.***
*This demonstrates how wide a range of estimates people produce, even when there is an answer.*

***Exercise 2: Estimate the diameter of the Earth, given that the distance from Christchurch NZ to Manchester UK is 18,800 km.***
*This demonstrates that with a bit of extra information it is possible to at least scale the answer to a rough order of magnitude. Those with a little maths ability will be able to work out an approximate answer from the information provided.*

*Estimate task duration using group*
Projects in which it is desired to have a better understanding of the risk in duration can make use of multiple rather than single estimates. A group of experts each give their own opinion of the duration of the task, and these are combined to produce a more robust estimate of task duration. In principle this appears to be a good idea.

However, the input opinion of each individual will generally be a subjective value judgement (Horlick-Jones, 1998; Pidgeon, 1998; Slovic, 1998), incorporating assumptions taken for granted (Jasanoff, 1998).

***Exercise 3: In a group, estimate the diameter of the moon.***
*This demonstrates the difficulty of combining multiple different estimates when people are all equally confident (unconfident).*

Thus the difficulty is in finding a suitable mechanism to combine the multiple different opinions. Systems based on voting, weighting, and consensus are potential candidates. However, they all have significant detriments. Voting is simple, but vulnerable to groupthink[2] (Robbins, Millett, Cacioppe, & Waters-Marsh, 2001 p302). Weighting is a popular mechanism, but has major difficulties in determining the weights without resorting to subjectivity by a judge. Consensus is good, but may not be achievable.

The model of Bley et al addresses one aspect of this problem, namely the collation of expert risk assessments (Bley, Kaplan, & Johnson, 1992). Another related development, for engineering decision making, is that of Ullman and collaborators (Ullman, 2001, 2002, 2003; Ullman, Herling, & D'Ambrosio, 1997).

[2] Group cohesion to common values (e.g. loyalty to management objectives) overwhelms the dissenting voices

There are several methods of coping with uncertain duration during the planning stage (Herroelen & Leus, 2005), as follows. Examples are given based on the simple Gantt chart of Figure 1.

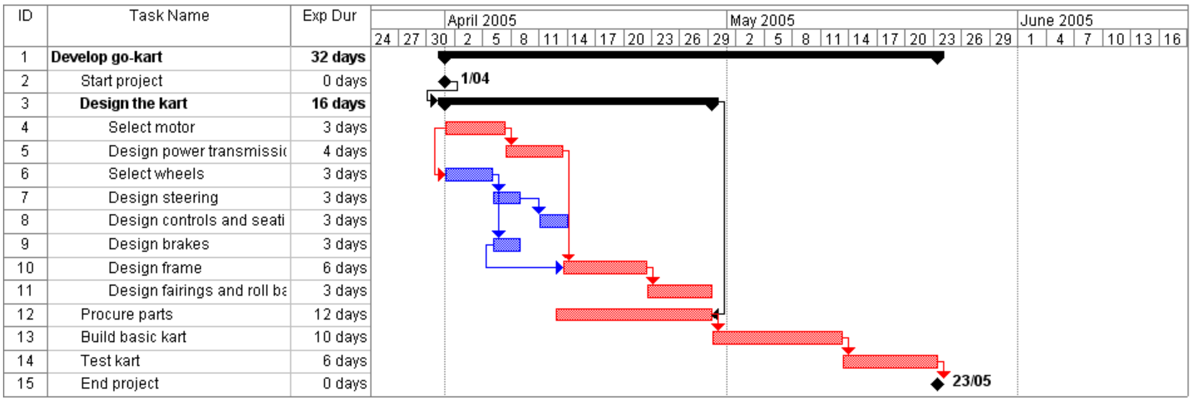


*Figure 1: Gantt chart for an illustrative project, showing tasks, expected durations, the schedule of those tasks on a calendar. The critical path is tasks 4, 5, 10, 11, 13, 14: these are the tasks which if delayed will delay the final completion data. The expected duration for this project is 32 days. This is a deterministic estimate because it does not acknowledge any uncertainty.*

***Exercise 4: With the person next to you, estimate the lower, expected and upper values (RANGE) for the land area of New Zealand [sq km].*** *This demonstrates the difficulty of making range estimates (see body of text).*
*Answer 268,021 sq km* http://www.infoplease.com/ipa/A0107834.html

*Estimate upper and lower limits of duration*

The first activity in moving beyond a single deterministic estimate of duration is usually to estimate the upper and lower limits of duration, for each task. The nominal duration would also be set if not done previously. The output is then the worst, typical and best estimates for duration, at individual level (see Figure 2) and for total project duration (see Figure 3).

| | A | B | C | D |
|---|---|---|---|---|
| 1 | **Develop go-kart** | | | |
| 2 | PERT analysis | ***Estimates [days]*** | | |
| 3 | *Critical path* | *Best* | *Nominal* | *Worst* |
| 4 | Formulae | | | |
| 5 | Select motor | 3 | 3 | 10 |
| 6 | Design power trans | 1 | 4 | 8 |
| 7 | Design frame | 3 | 6 | 15 |
| 8 | Design fairings | 2 | 3 | 15 |
| 9 | Build basic kart | 5 | 10 | 15 |
| 10 | Test kart | 2 | 6 | 10 |
| 11 | *Project duration* | *16* | *32* | *73* |

*Figure 2: A range of estimates may be given for each task. These are the optimistic (best), expected (nominal), and pessimistic (worst) cases. A crude estimate of the range for the overall project duration is obtainable by summing the estimates for those tasks on the critical path.*

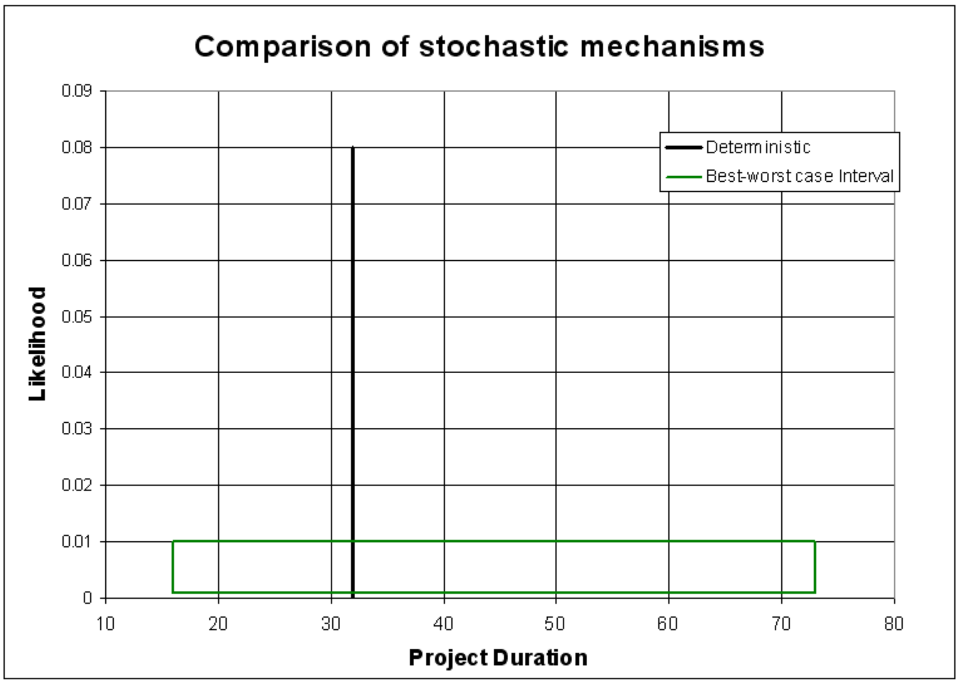


*Figure 3: Optimistic and pessimistic estimates may be used to determine the interval (rectangle in the figure) for project duration.*

Applying this method results in excessively conservative estimates of the range of the whole project. This is because of the unlikeliness of all durations being simultaneously either at best or worse cases. For example, the optimistic project duration (16d) requires that all durations take up their optimistic values, which is very unlikely. It is more likely that the real project will have a mix of durations, some tending towards the optimistic, others to the pessimistic.

Consequently, most project managers would not place any reliance on the overall project duration predicted by this method. Instead they would use another method (e.g. PERT, described next). Nonetheless, there is an almost universal reliance on the underlying principle of *optimistic, expected, and pessimistic* estimates. This is problematic since risks are introduced at this estimating stage: Unreliability of the estimates, and Ambiguous interpretation:

(a) *Unreliability of the estimates*
Estimates are generally unreliable because data on which to base the estimates are usually unavailable. Consequently, the estimates are often nothing more than guesses, and just as likely to be inspired by emotional state of mind, personal objectives, personal attitudes to risk, and organisational politics as by experience and rationality. Furthermore, the estimates are based on the protagonist's perceptions of probability, which is challenging to many especially when trying to assess extreme events that have never been actually experienced. Estimating extreme values is also vulnerable to several biasses: anchoring/centering (fixate on the nominal value and unable to anticipate the full range that could be possible), representativeness (fixation on a value that is familiar, e.g. the time taken in the last project), and optimism/pessimism (Vose, 1996).

(b) *Ambiguous interpretation*
Estimates are generally also ambiguous. What exactly is a minimum or maximum value anyway? Is it the typically expected value, or the maximum conceivable? The interpretation significantly affects the overall schedule variability. Further trouble comes when multiple people, each with their own interpretation, are involved with providing duration estimates. This type of problem has been identified in the risk assessment literature (Pate-Cornell, 1996; Vose, 1996), where it is generally accepted that minimum and maximum values are weak (though appropriate in non-critical areas), but are highly problematic when external scrutiny and public participation are involved because they are hard to defend. Some have suggested that a better way is to assign a cumulative probability to each estimate, (e.g. 99% Meredith & Mantel, 1995 p 394). While this is ideal, it is difficult to achieve. People cannot estimate the magnitude of such an extreme event, one seldom actually encountered, with anything but a personal guess. Nor is it easy for people to distinguish fine graduations of likelihood, e.g. 99% vs 99.5%, but unfortunately it is precisely at the tails of a distribution that such accuracy is most important.

These two risks are seldom explicitly identified in project management. Unfortunately they may compromise the accuracy of the downstream attempts to handle the uncertainty, as the follows.

*Apply PERT*

The most common probabilistic method is the project evaluation and review technique (PERT). However, it is not a full probabilistic method since it uses moment methods (based on the mean).

The PERT process is to combine the three estimates of duration (optimistic, expected, and pessimistic) into a single time estimate, the mean. PERT does this by fitting a beta distribution to the three estimates. The worst and best case estimates correspond to the end bounds of the beta (not the 99% cumulative probability as is sometimes believed (Meredith & Mantel, 1995)), and the nominal estimate corresponds to the mode. Selection of the beta is simply for convenience, since it is bounded on both sides (unlike the normal), and its standard deviation is easily determined from the end points (again unlike the normal).

| ID | Task Name | Duration | Optimistic Dur. | Expected Dur. | Pessimistic Dur. |
|---|---|---|---|---|---|
| 1 | **Develop go-kart** | **36.17 days** | **16 days** | **32 days** | **73 days** |
| 2 | Start project | 0 days | 0 days | 0 days | 0 days |
| 3 | **Design the kart** | **20.17 days** | **9 days** | **16 days** | **48 days** |
| 4 | Select motor | 4.17 days | 3 days | 3 days | 10 days |
| 5 | Design power tra | 4.17 days | 1 day | 4 days | 8 days |
| 6 | Select wheels | 3 days | 1 day | 3 days | 5 days |
| 7 | Design steering | 3 days | 1 day | 3 days | 5 days |
| 8 | Design controls ἀ | 3 days | 1 day | 3 days | 5 days |
| 9 | Design brakes | 3 days | 1 day | 3 days | 5 days |
| 10 | Design frame | 7 days | 3 days | 6 days | 15 days |
| 11 | Design fairings a | 4.83 days | 2 days | 3 days | 15 days |
| 12 | Procure parts | 12.33 days | 5 days | 12 days | 21 days |
| 13 | Build basic kart | 10 days | 5 days | 10 days | 15 days |
| 14 | Test kart | 6 days | 2 days | 6 days | 10 days |
| 15 | End project | 0 days | 0 days | 0 days | 0 days |

*Figure 4: PERT requires the project manager to provide three estimates for each task: the optimistic, expected, and pessimistic. The software (in this case MS Project®) then calculates the best guess for 'duration' using weighting factors provided by the user.*

PERT then determines the project completion date by summing all the newly calculated mean durations for all tasks on the critical path (Taylor, 1999). It relies on the central limit theory (CLT), which assumes task independence, and permits the means to be summed. (The CLT permits any approximately normal shaped distribution to be used - it only needs the mean and standard deviation, i.e. the moments, of whatever distribution is used).

Software, e.g. Microsoft Project® (MSP, 2003), may be used to perform PERT calculations, as shown in Figures 4 and 5. These show the three estimates, the resulting calculated duration, and the Gantt chart.

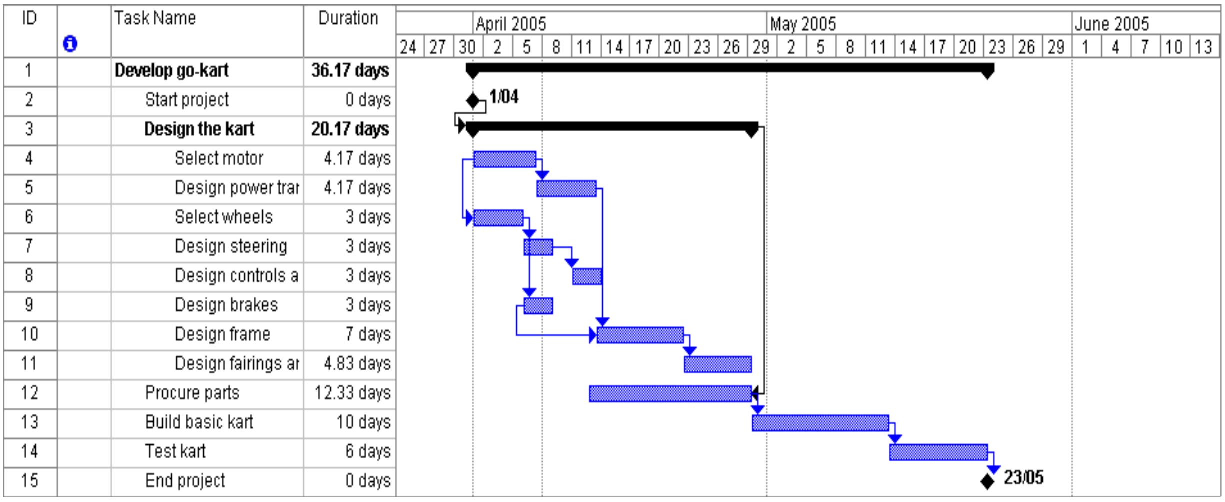


*Figure 5: Gantt chart for PERT analysis. Calculated mean durations have been inserted by the software in place of the nominal values first provided (see 'expected dur.' in previous figure). The project duration has become longer than before, because individual task durations have lengthened, in turn due to the effect of the pessimistic estimates.*

The CLT also permits the standard deviation to be determined for the total project duration, as the square root of the sum of the individual variances.[3] For this it is necessary to determine the standard deviation of each task duration. This is easy to do, thanks to the beta distribution. However, the PERT implementation in MS Project® is lightweight, since it cannot do this. Instead it is necessary to perform an external calculation of project standard deviation, e.g. with a spreadsheet, the results of which are shown in Figures 6 and 7.

| | A | B | C | D | E | F | G |
|---|---|---|---|---|---|---|---|
| 1 | **Develop go-kart** | | | | | | |
| 2 | PERT analysis | ***Estimates [days]*** | | | ***Calculated results*** | | |
| 3 | *Critical path* | *Best* | *Nominal* | *Worst* | *Expected duration* | *Variance* | |
| 4 | Formulae | | | | *((Worst+4xNominal+Best)/6)* | *((Worst-Best)/6)* | |
| 5 | Select motor | 3 | 3 | 10 | 4.17 | 1.167 | |
| 6 | Design power trans | 1 | 4 | 8 | 4.17 | 1.167 | |
| 7 | Design frame | 3 | 6 | 15 | 7.00 | 2.000 | |
| 8 | Design fairings | 2 | 3 | 15 | 4.83 | 2.167 | |
| 9 | Build basic kart | 5 | 10 | 15 | 10.00 | 1.667 | |
| 10 | Test kart | 2 | 6 | 10 | 6.00 | 1.333 | |
| 11 | *Project duration* | *16* | *32* | *73* | *36.17* | | |
| 12 | Project variance | | | | | 9.500 | Sum of task variances |
| 13 | Project standard deviation | | | | | 3.082 | Square root of project variance |

*Figure 6: PERT analysis for project variance, calculated in a spreadsheet. The project standard deviation (bottom right) may then be used to create a normal distribution and determine likelihood of various scenarios. For example, with some basic statistics it can be estimated that there is a 90% probability that the actual project duration will be between (lower limit) 31 day and (upper limit) 41 day. This is a big improvement on the simple best-worst case interval.*

PERT has become something of an ingrained habit in project management, one that is used without question. There are more powerful methods for coping with stochastic uncertainty in duration, discussed below.

PERT has several limitations. One is that the critical path is fixed. PERT is unable to accommodate the fact that the critical path itself may change, i.e. other tasks may come onto the critical path as durations adjust. Furthermore, the PERT algorithm, which uses the beta distribution, is only an approximate probabilistic computation method[4]. It gives some indication of the central tendency (mean) and dispersion (standard deviation), but uses moment

[3] 'Variance' in this case refers to the statistical term for dispersion of the distribution, i.e. the square of the standard deviation, and not to the project management term which is difference between planned and actual outcomes e.g. as used in MS Project.

[4] Three estimates are used in PERT to determine a mean expected time using a beta distribution in which the mean is typically t = (a+4b+c)/6 where a, b, c are the minimum, most likely, and maximum times respectively. Values other than '4' and '6' are possible (Vose, 1996). The mean expected time is then used in the network as a deterministic value. The variance for each activity is v = ((c-a)/6)^2 for the beta distribution. The total project time has a normal distribution (as per the central limit theorem) with variance given by the sum of the variances of the activities on the critical path (Taylor, 1999, p463).

methods which are approximate. Nor is there any underlying theoretical justification for using the beta rather than any other distribution, except convenience for the analyst. In many ways this does not need to be a problem, given the large uncertainties listed above. However, if the data support it, and a precision analysis is required for duration, then the following methods are superior.

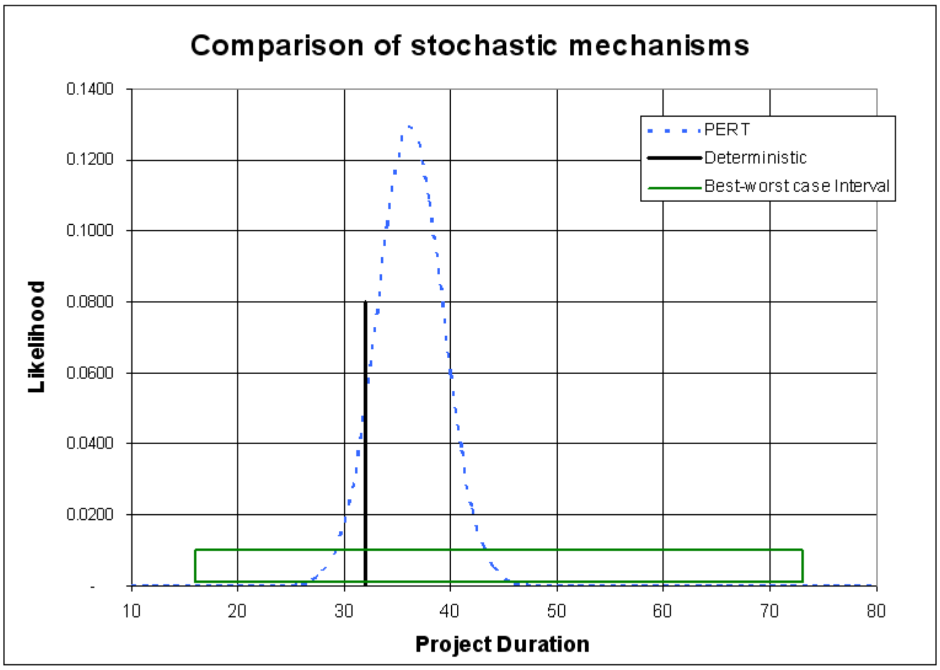


*Figure 7: PERT analysis produces a tighter estimate of the project duration than a simple best-worse case interval. The PERT estimate has a mean of 36 days, and suggests that there is really not much chance that the real duration will at either extreme.*

*Apply possibilistic method*

Fuzzy theory (5) may be applied to determine uncertainty in project duration. This feature is unavailable in software such as MS Project, and would have to be done with other special tools. Fuzzy theory is a possibilistic rather than probabilistic method.

A fuzzy set represents membership across an interval: it 'records the possibility that a given value could be in the set, and consequently many range variables may all have a possibility of unity. By comparison, a probability density instead has unit area under the curve' (Pons & Raine, 2003 p532). Fuzzy sets are usually triangular or trapezoidal, as uniform (rectangular) sets tend to misbehave.

For example, the sample project plan be analysed with fuzzy cut set theory, as follows. First, the critical path is identified as activities 4, 5, 10, 11, 13, 14. Next, fuzzy sets are asserted for each of these variables. For ease of comparison, beta distributions were used with the same parameters as before, and these distributions were then fuzzified, i.e. scaled so that the likelihood of the mode was unity. Then the total project duration was calculated as the sum of the durations on the above critical path. The DSI-fuzzy engine was used (Pons & Raine, 2003). The results for project duration are shown in Figure 8.

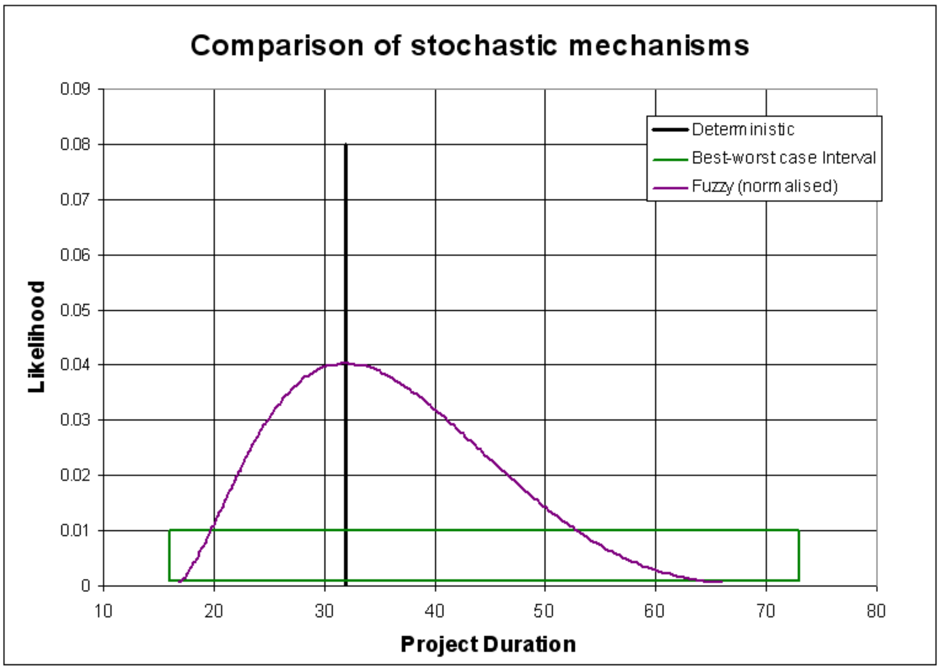


*Figure 8: Fuzzy analysis produces a tighter estimate of the project duration than a simple best-worse case interval. However the two methods have the same outer bounds, it's just that the fuzzy method puts more weight in the centre and less on the tails. Note also that the mode (highest peak) of the fuzzy result always corresponds exactly to the deterministic estimate of duration (32d in this case), which is an appealing feature. (By comparison the probabilistic methods give a mean of about 36 days).*

Fuzzy theory has benefits but also some detriments. The benefits are that indecision ('imprecision') about the precise value of a parameter (e.g. duration) is arguably better represented by a fuzzy set of possibilities (hence possibilistic) rather than a probability distribution. This is because probability distributions are strictly only for representing frequency of random events. Fuzzy advocates assert that the uncertainty inherent in indecision is not a random variable, though others disagree. The detriment of fuzzy theory is that there is no underlying theoretical reason why uncertain intervals should have any particular shape, including triangular or trapezoidal. These two are just used for convenience (the normal distribution is irrelevant in fuzzy theory). Nor is fuzzy theory able to cope with all types of distributions, e.g. it misbehaves with uniform and multimodal distributions. By comparison the probabilistic approaches are not limited in the distributions they accept, and they have the added advantage that there can be strong underlying validity for the normal distribution in particular.

Nonetheless fuzzy theory has been applied extensively in engineering and decision making, where it is noted that 'the Fuzzy cut set approach is possibly the method of choice where the inputs are opinions rather than sampled/estimated frequencies, rapid assessment is required, and the precise shape of the uncertainty is not needed' (Pons & Raine, 2003 p536). There are examples of fuzzy theory being applied to project management (Zheng & Ng, 2005).

*Apply probabilistic method*
The most theoretically robust way to determine stochastic uncertainty, assuming the variables are random, is one of the probabilistic methods. There are actually three, but one dominates.

The mathematically precise method is the algebra of random variables (Springer, 1979; Syski, 1989). This becomes impractically complex for all but the addition of normal distributions. Within these limitations it could be applied to determine project duration, though applications are generally financial (Sarper, 1994).

The most popular practical method is Monte Carlo simulation. It involves assigning a full probability distribution (not just the moments as in PERT) to each uncertain variable, e.g. task duration. The simulation then takes a single random sample from each distribution, and determines the total project duration. If programmed accordingly, the algorithm can also determine the new critical path. The process is repeated numerous times to build up a histogram for the total project duration (Pons & Raine, 2003). There have been many research applications (Shih, 2005). The method is embodied in software, e.g. @Risk® (Pallisade, 2005) , Analytica® (Lumina, 2005). The sample project plan was analysed with Monte Carlo simulation. As before, the critical path is 4, 5, 10, 11, 13, 14, and beta distributions were used. Then the total project duration was calculated as the sum of the durations on the critical path. The @Risk® software was used within a MS Excel® spreadsheet (see Figure 9), eventually producing the result shown in Figure 10.

| | A | B | C | D |
|---|---|---|---|---|
| 1 | **Develop go-kart** | | | |
| 2 | | | | |
| 3 | *Critical path* | *Mean duration* | | *Formulae* |
| 4 | Select motor | 4.167 | | RiskPert(3, 3, 10) |
| 5 | Design power trar | 4.167 | | RiskPert(1, 4, 8) |
| 6 | Design frame | 7.333 | | RiskPert(5, 6, 15) |
| 7 | Design fairings | 4.833 | | RiskPert(2, 3, 15) |
| 8 | Build basic kart | 10.000 | | RiskPert(5, 10, 15) |
| 9 | Test kart | 6.000 | | RiskPert(2, 6, 10) |
| 10 | *Project duration* | *36.500* | | RiskOutput() + SUM(B4:B9) |
| 11 | | | | |

*Figure 9: Model for project duration as represented in a spreadsheet using @Risk.*

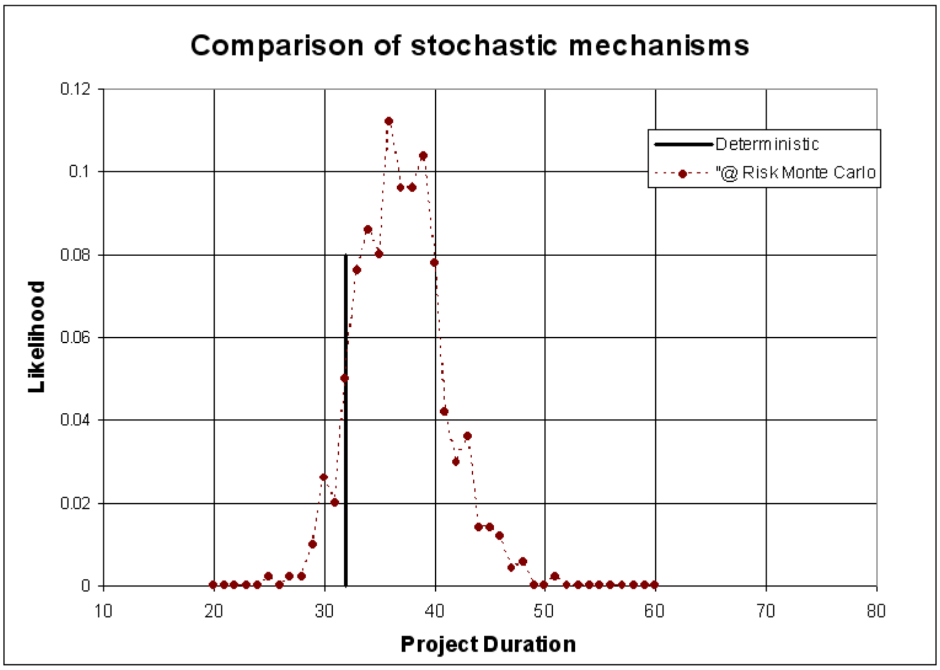


*Figure 10: Monte Carlo simulation result for total project duration, using @Risk. Note the characteristic roughness to distributions produced with the Monte Carlo method: this is an artefact of the random sampling process. Mean value is 36.5 days. Many other statistics are available, including the mode (35.3 d).*

Importantly, Monte Carlo does not have to assume independence of the variables. For example, if bad weather affects more than one task, then that can be accommodated, whereas PERT does not. Also important is the ability to dynamically determine the critical path. Hence its popularity and widespread application (Basu, 1998; Croll, 1995; Finley & Fisher, 1994; Vose, 1996). However, these advanced features require special attention by the analyst, perhaps even software programming, and are not available within software such as MS Project ®.

Detriments of Monte Carlo simulation are that probability distributions are not necessarily a valid way of expressing uncertainty in task duration (see fuzzy theory above). Recall also the estimating errors above. So, though it presents impressively accurate results, the relevance is not automatic.

The third probabilistic method is based on discrete combinatorial methods (Cooper & Chapman, 1987). It is a relatively obscure mechanism, but has been applied to engineering design as 'design for system integrity' (DSI), and has advantages over Monte Carlo in some features (Pons & Raine, 2003). Applying this method to the sample project gives results shown in Figure 11.

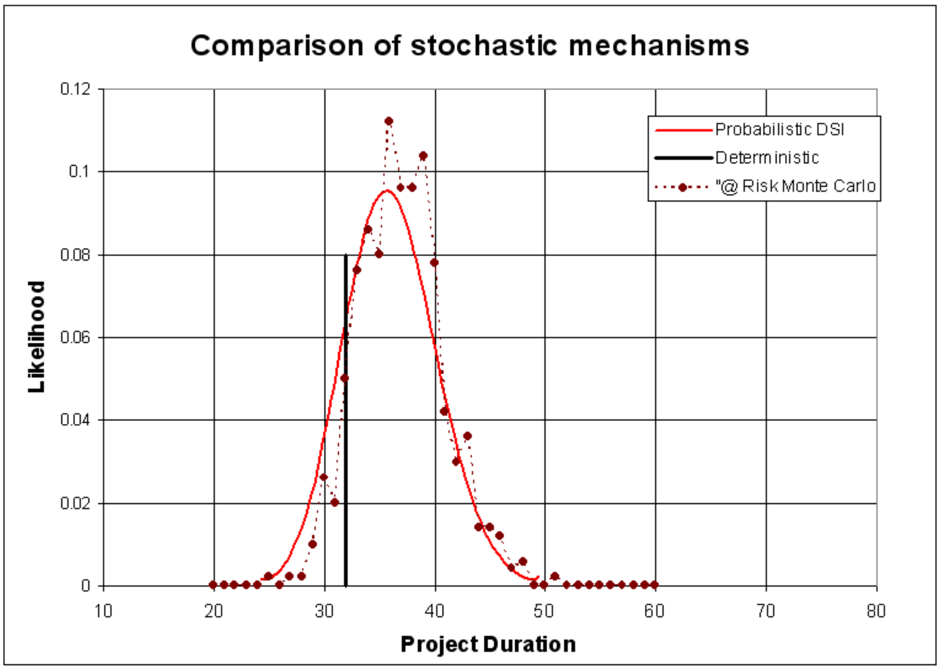


*Figure 11: Result for total project duration, using controlled interval simulation with DSI. Note the characteristic smoothness of the distribution produced with this method. Mean value is 36.0 days.*

## 4 Discussion

Several methods have been shown for simulating the stochastic uncertainty in project duration. Each has benefits and detriments. The results for each method, for the sample project being analysed, were projected onto the same axis to facilitate comparison (see Figure 12).

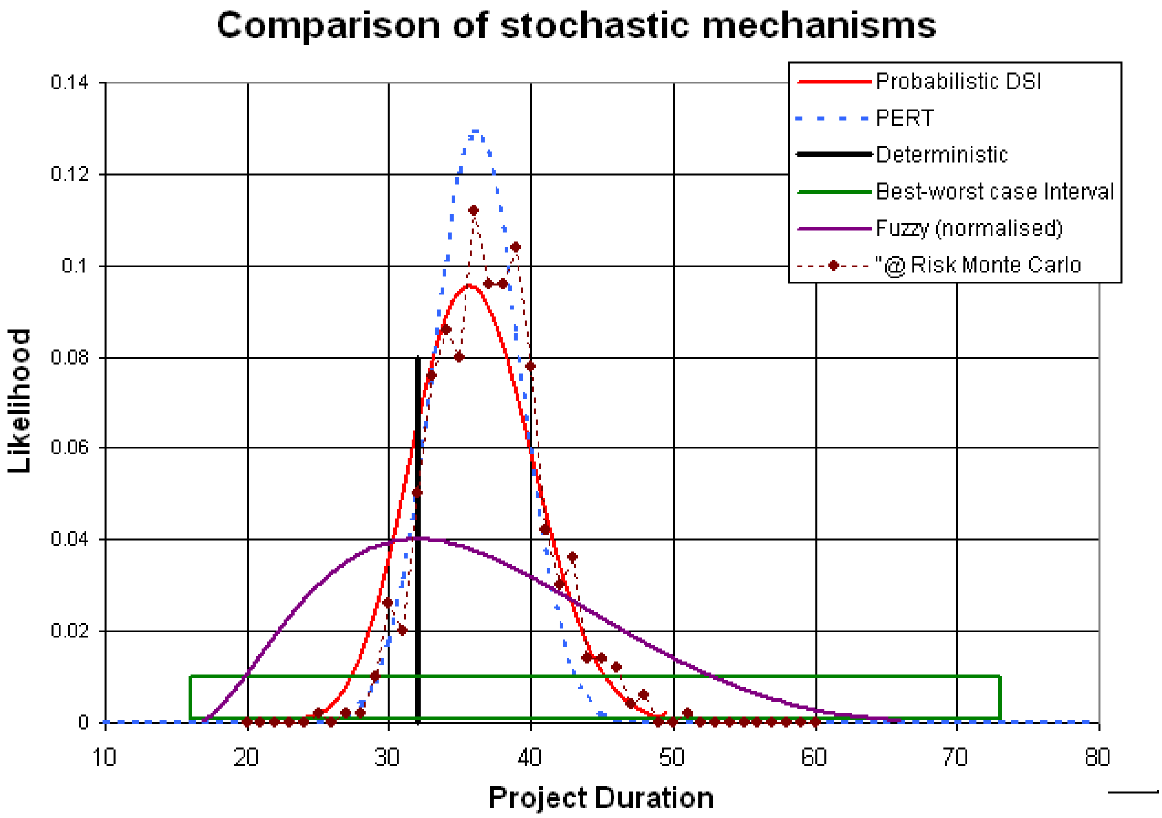


*Figure 12: Comparison of multiple methods of estimating duration.*

Some observations follow:

- The Deterministic estimate (32d) is the typical method used in project management. It is simple and easy to use, but fails to show duration risk.
- The best-worst case project interval (16-73 d) is readily determined, e.g. by MS Project. However, it is practically worthless as it fails to show any likelihood.
- The fuzzy theory estimate (32 d mode) is effectively a shaped interval, and is therefore much superior to a best-worse case interval. The fuzzy result covers the full range of the best-worse case interval, but has lighter tails. Nonetheless, fuzzy theory over represents the risk of extreme outcomes (see the greater likelihood in the upper and lower tails), at least compared to the probabilistic methods.
- PERT (36.17 d mean) produces a reasonable probabilistic estimate, but it under represents the risk of extreme outcomes (lighter tails than full probabilistic methods). This would seem a disadvantage.
- Monte Carlo (36.5 d mean) produces a probabilistic result, but this is partly obscured by large random artefacts. This is problematic if the likelihood of extreme events is being investigated, since Monte Carlo will not reliably detect these, unless the number of iterations is substantially increased. The mean is also variable from run to run.

- DSI (36.0 d mean) also produces a probabilistic result. Benefits are a smooth curve, and good representation from the upper and lower tails for less computational effort than Monte Carlo.

There are several figures of merit, and unfortunately one method does not dominate:

| ***Figure of merit*** | ***Recommended method*** |
|---|---|
| *Accuracy and precision of distribution for modelling rare events*: | DSI probabilistic. Monte Carlo with more iterations could get similar accuracy. |
| *Conservative, but not unreasonably so:* | Fuzzy theory |
| *Quickest estimate of the mean:* | PERT, but greater risk of under representing extreme events. |
| *Ability to include branching conditional statements (e.g. changed critical path)*: | In principle PERT, fuzzy, Monte Carlo, but requires custom implementation, i.e. expert analyst. |

However, all of this is questionable given the high uncertainties in estimating the parameters of the distribution in the first place. If the raw input estimates are only rough, then why use a precision statistical tool thereafter? This important point is too often lost. For those comparatively few cases where robust probability estimates exist, based on firm experience, then Monte Carlo would be recommended. However, , when estimates are only guesses, as is often the case in project management, then fuzzy theory would be the best method, and superior to PERT.

Project management software would do well to abandon its fixation with PERT, and instead adopt fuzzy theory, because:

(a) project management estimates often include an element of indecision with the random variability,
(b) fuzzy theory and PERT are of comparable accuracy (and inaccuracy),
(c) fuzzy theory mode (highest peak) of the fuzzy result always corresponds exactly to the deterministic estimate of duration, which simplifies interpretation.

Design projects do not always respond well to project management. Design engineers have to work with incomplete and subjective information, and it may be impossible to plan out the activities beforehand in any great detail. Solution paths are explored partially, and perhaps abandoned. Prior tasks have to be reworked. The conventional project management methods ignore rework activities, assume predictable tasks and duration, and cannot suggest concurrent activities (Yassine, Falkenburg, & Chelst, 1999). Prototype methods such as design structure matrix (DSM) (Yassine et al., 1999) have been shown to overcome some of these limitations and may yet enter main-stream project management.

The problem for design is that epistemic uncertainty is high, i.e. the behaviour of the proposed technical system is poorly understood. By comparison project management only accommodates stochastic uncertainty. This is the variability that comes from being uncertain about the duration for a task. Epistemic uncertainty is more problematic than stochastic uncertainty. It is difficult to anticipate in project management, although relatively easy to monitor.[5]

## 7 Conclusions

Several methods have been shown for coping with uncertain estimates of duration, namely PERT, fuzzy theory, and probabilistic computations (three sub-types). The limitations for PERT were identified and it was concluded that fuzzy theory would be a better computational engine than PERT for routine project management use.

Also, two major risk areas were identified with all stochastic estimating processes: the unreliability of the estimates, and the ambiguous interpretation of the lower and upper limits.

*Implications for project managers*
Setting a simple deterministic estimate of task duration is typical in real project management. Yet with a little extra effort the uncertainty in those estimates can be captured. The simplest way to do this is using PERT, which is already provided within project management software. Thus project managers might benefit from greater familiarity with PERT.

It has been shown that there are more powerful methods than PERT, e.g. fuzzy theory and Monte Carlo. However, these require specialised skills and are currently not practical for most project managers. Thus all but the specialist project managers might be best to stay away from these other methods, but keep a watch for future developments, especially fuzzy theory.

*Implications for researchers*
Software implementations of PERT are lightweight, at least in MS Project ®. It is too complex for most users. Software developers need to implement PERT better, and should also consider implementing fuzzy theory.

*Implications for design managers*
Complete initial scope definition is generally impractical for this domain. Designers encounter technical difficulties along the solution path, and divert to other solutions, causing major changes to project planning and even to scope. Rather than attempting to put major effort into a perfect project plan, designers tend to proceed with a sufficient plan, and adapt it as needed in response to environmental changes. Thus design managers might be best to aim for adequate rather than exhaustive project plans, scope definitions and risk assessments. They might complement this by active project monitoring to give flexible, fast, efficient and effective response during deployment.

**Answers to exercises**

(1) *Diameter of earth 12,760 km or 7,926 mi*
(2) *Estimated diameter of earth D = P/pi = 2 x 18,800/pi = 12,000 km*
(3) *Diameter of moon 3,476 km (2,160 miles)*
(4) *Land area of New Zealand 268,021 sq km, from*

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[5]The monitoring can readily be done using software such as MS Project, which provides a feature to save the intended plan ('baseline') and then show how the actual Gantt chart diverges from the intended one ('Tracking Gantt').

*http://www.infoplease.com/ipa/A0107834.html*

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