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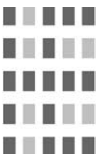

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ECONOMIC EVALUATION

Alternative decision modelling techniques for the evaluation of health care technologies: Markov processes versus discrete event simulation

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Summary

Markov models have traditionally been used to evaluate the cost-effectiveness of competing health care technologies that require the description of patient pathways over extended time horizons. Discrete event simulation (DES) is a more flexible, but more complicated decision modelling technique, that can also be used to model extended time horizons. Through the application of a Markov process and a DES model to an economic evaluation comparing alternative adjuvant therapies for early breast cancer, this paper compares the respective processes and outputs of these alternative modelling techniques. DES displays increased flexibility in two broad areas, though the outputs from the two modelling techniques were similar. These results indicate that the use of DES may be beneficial only when the available data demonstrates particular characteristics. Copyright © 2002 John Wiley & Sons, Ltd.

Keywords economic evaluation; decision modelling; Markov processes; discrete event simulation

Introduction

Modelling, as a decision analytic tool, is a key appliance in the health economists' toolbox [1]. The critical evaluation of the modelling process has been the subject of increasing attention in recent years [2–5], but only brief regard has been paid to the appropriate choice of decision modelling technique and the consequences of the choice have not been fully explored [2,6]. This situation is partially explained by the limited range of decision analytic modelling methods employed by health economists as demonstrated by a recent paper that reviewed modelling economic evaluations published in 1997 [Barton P, Robinson S, Bryan S. The use of modelling in the economic evaluation of health care. *Health Econ*, forthcoming]. Of the 119 papers reviewed it was reported that 76 (64%) employed decision trees, 43 (36%) used Markov processes and only 2 (2%) reported the results from discrete event simulation (DES) models. A brief review of Medline identified two further economic evaluations that employ DES that have been published since 1997 [7,8].

The characteristics of decision trees and Markov processes are very different and the choice between the two techniques in alternative treatment settings is relatively straightforward. With the introduction of DES to the field of economic evaluation in health care the issue of choosing the appropriate technique could become an important decision in the initial stages of modelling projects. Both DES models and Markov processes are forms of simulation, but DES allows more complicated representations of the system being modelled [7].

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Within a DES model, patients move through the model, experiencing events at any discrete time period after the previous event. The analysis of the model is triggered by the occurrence of an event, at which point the model asks what and when is the next event for this patient, rather than a Markov process, which asks what events are occurring at regular intervals.

This paper aims to compare the use of a Markov process and a DES model to represent patient pathways over extended time horizons in terms of the process and output of economic evaluations of health-care technologies. Criteria on which the choice of modelling technique can be assessed have not been discussed in the literature, but intuitively there are two such criteria – flexibility and analytic input. Each covers various aspects:

- Flexibility describes how well the model adapts to different forms of input data and interrelationships between parameters. This criterion reflects how closely a particular modelling technique allows the reality of patient pathways to be modelled.
- Analytic input relates to the level of complexity in building the model in terms of the expertise and the amount of time required. This criterion also describes the ease with which modifications to the model can be made, both to the actual structure of the model and to the incorporation of alternative formats of model inputs.

The alternative modelling techniques are applied to an economic evaluation that compares tamoxifen and chemotherapy versus tamoxifen alone in node positive, postmenopausal women aged under 65, full details of the data used in the evaluation are available in a published paper [8]. Breast cancer is the commonest female cancer in the United Kingdom with around 33 000 newly diagnosed cases and 15 000 deaths from the disease each year [9]. Following diagnosis of breast cancer in the breast and/or axilla a proportion of patients will be 'cured' by local treatment. However, there is a risk of micrometastatic disease, present in distant areas, causing systemic relapse. The aim of adjuvant therapy is to destroy this subclinical disease [10]. The main objective of adjuvant therapy for breast cancer is to prolong survival while maintaining a high quality of life [11].

The comparison of the modelling techniques is also presented in the context of a stochastic evaluation. The objective of a stochastic analysis is to obtain a distribution of each of the model's outputs that are informed by randomly sampled sets of input parameter values from the specified probability distributions. The remainder of the paper assumes that the reader is informed about the concept and conduct of stochastic cost-effectiveness analyses, though details on the methods used to specify the input distributions are provided below. The interested reader is referred to a number of papers that have described the use of stochastic evaluations (alternatively labelled probabilistic sensitivity analyses) [12–15].

Methods

The choice of approach to building the alternative models was based on the premise that the health economist wishes to retain control of the decision model, which meant that the modelling techniques adopted were accessible to analysts with no formal training in operations research. The Markov process was built in Excel using a risk analysis programme add-in [16]. A similar model could have been built in Excel without the risk analysis programme, but the add-in provided more flexibility with respect to the choice of input probability distributions. It was analysed as a cohort analysis because this was the most common form of analysis in the economic evaluation literature, but also because the more complicated first-order Monte Carlo simulation approach does not provide additional information for the allocation of resources [17]. The DES model was built using software designed specifically to create DES models, because such software provides guidance to the use of DES and facilitated the easiest construction of such models without the loss of any of it's capabilities [18].

The structure of the models was based on the inclusion of events that have a significant impact on the outcomes of the model. Information on the relevant events included in the decision model was sought from health professionals as well as a preparatory review of the breast cancer literature and the Internet [8]. The alternative model structures relating to the Markov process and the DES model are presented in Figures 1(a) and 1(b). The only difference between the two model structures is the inclusion of the toxicity states as events within the patient pathways in the Markov

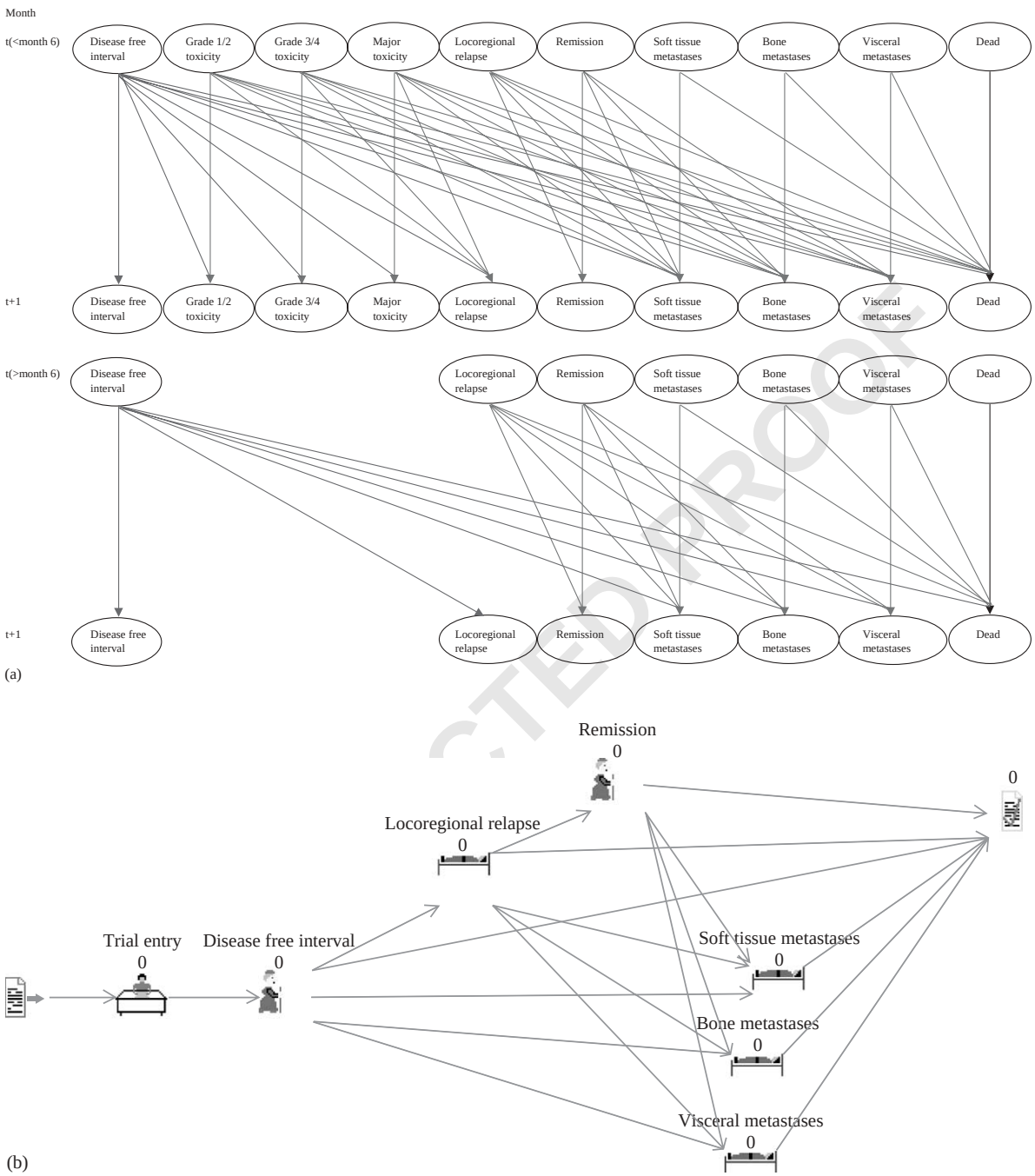

Figure 1. (a) Representation of the possible patient pathways within the Markov process. (b) Representation of the possible patient pathways within the DES model

process. Toxicity is included in the DES model, but is captured as attributes within the health state disease free interval (DFI) (this approach was adopted for the DES model in order to represent the available data in a more intuitive manner, as is described in more detail below). Despite this

Table 1. Respective assumptions employed in the case study models

Area	Markov process	DES model
General	• Cycle length of 1 month. • Patients aged 50–59 years on entry to model, maximum age in model 100.	• Minimum time period of 1 month. • Patients aged 50-59 years on entry to model, maximum age in model 100.
Disease free interval	• Annual probability of leaving DFI informed by survival curve. • Annual probabilities converted to monthly probabilities assuming constant transition rates.	• Annual probability of leaving DFI informed by survival curve. • Annual probabilities converted to monthly probabilities assuming constant transition rates.
Toxicity	• Patients can experience any combination of three categories of toxicity. • Grade $\frac{1}{2}$, $\frac{3}{4}$ toxicity end after 6 months, length of major toxicity sampled from probability distribution.	• Patients can experience any combination of three categories of toxicity. • Grade $\frac{1}{2}$, $\frac{3}{4}$ toxicity end after 6 months, length of major toxicity sampled from probability distribution.
Locoregional relapse and ensuing remission	• Patients remain in locoregional relapse for exactly 1 month. • A mean time spent in remission employed. • Patients subject to a constant monthly probability of leaving the remission state.	• Patients remain in locoregional relapse for exactly 1 month. • Annual transition probability informed by survival curve. • Annual probabilities converted to monthly probabilities assuming constant transition rates.
Metastases	• A mean time spent in metastatic states employed. • Patients subject to a constant monthly probability of dying.	• A mean time spent in metastatic states employed. • Patients remain in metastatic states for set amount of time.

difference in specification the pathways described by the two models are identical. All patients start the model in the health state DFI. During the first 6 months patients in the DFI state can experience toxic effects caused by the adjuvant therapies, a relapse in one of the four specified sites of relapse – locoregional, soft tissue, bone or visceral, or they can die from a cause other than breast cancer. At the end of the first 6 months the patients in the toxicity states are assumed to return to the original DFI state.

Although the pathways within the two models are the same the assumptions relating to the transitions between the health states differ in a number of cases. Table 1 presents the assumptions made with respect to different stages of the models, whilst the following sections describe the assumptions in more detail.

General assumptions

The specification of a minimum time period of advancement was required for the DES model, as well as a cycle length for the Markov process. Although a case could be made for differential timing on the basis of model running time, it was decided that the patient pathways could be most accurately represented in both models using a time period of 1 month. The patient population for both models was aged between 50 and 59 with a single age being sampled for each iteration of the model. A similar time horizon for both models was also implemented with patients living to a maximum of 100 years.

Disease-free interval

The choice of 1 month as the models' cycle length meant that the annual probabilities describing the length of DFI needed converting to monthly probabilities. Transition rates were assumed to remain constant over the year, because no data were identified that contradicted this assumption. Disease-free survival (DFS) data were identified

for the first 15 years post-diagnosis, after which time the patients were assumed to remain disease free and die at the same rate as the general population. Both models described these actions identically.

Toxicity

The available data describing the incidence of toxicity referred only to the proportion of all patients that experienced different forms of toxicity, specified in the models as grade 1 or 2, grade 3 or 4, and major, not the proportion of patients experiencing different combinations of toxicities. In consultation with clinical colleagues it was agreed that the most intuitive assumption was to apply the individual probabilities of experiencing each category of toxicity to all patients, i.e. to assume conditional independence. The DES model was able to accommodate conditional independence by treating each form of toxicity as a separate attribute so that as patients entered the DFI state they were subject to experiencing any combination of the three toxicity attributes. To replicate the same assumptions in the Markov process, it was necessary to model seven toxicity states representing all the possible combinations of toxicity, and to estimate the respective joint probabilities from the available data based on an assumption of conditional independence. As in the DES model, three probability distributions were specified, the sampled values from these distributions were used to calculate the seven transition probabilities, which were scaled down if necessary.

Locoregional relapse and ensuing remission

Patients experiencing locoregional relapses were assumed to remain in that state for a maximum of 1 month, following which time they either entered a period of remission, or they experienced a more severe metastatic relapse, or they died from other causes. The data describing patients' progression from locoregional relapse was mainly in the form of DFS curves representing the probability of progressing in successive time periods (see [8] for references). To apply data from a survival curve to patients within a decision model it is necessary to record when separate patients enter a state in order to apply differential probabilities of experiencing an event over time. The Markovian assumption prevents the application of differential probabilities to patients within the same health state other than a state in which patients enter the model. In effect, a patient is a patient is a patient in every non-start state within the model. It would be possible to use multiple remission states to represent the different transition probabilities, whereby each cohort entering remission would move into a subsequent remission state in the absence of further relapse or death at the end of each month. Separate transition probabilities could then be applied to each remission state to reflect the length of time spent in remission. In the current model, however, where monthly Markov cycles were specified and 11 years of DFS data were available, such a solution would require the creation of 132 (11×12) remission states in order to assign the relevant probabilities. It was considered that most analysts using Excel would find the creation of such a number of repeat states impractical. Therefore, the DFS data was transformed to a constant probability that could be applied to every patient within the remission health state.

The ideal output from the conversion of the survival data is a mean length of DFS, which would produce, in the absence of discounting, the same mean results as those derived from the use of the survival curve directly. However, if the surviving proportion of patients presented by the survival curve does not reach zero, the conversion of survival curves to constant probabilities in the Markov process is approximate because mean 'survival' cannot be calculated precisely. On the advice of oncology colleagues the most satisfactory assumption was that patients remaining disease free at the end of the available follow-up period (11 years) follow the survival profile of the general population. This assumption was possible in the DES model because the model recorded the age of each patient as they entered the remission state, which enabled the application of age-specific mortality rates to each patient that survived beyond the last point of follow-up. In the Markov process it was not possible to determine the age of the patient at the end of the period of follow-up. A single time period spent in the health state was required for the whole patient group. The distribution of DFS was significantly skewed so the median DFS was an inappropriate proxy for the mean. Instead, the baseline estimate of DFS for the Markov process was based on simplified assumption that all patients remaining disease free

at the end of 11 years died after a further nine disease free years was used to estimate a mean period of DFS.

The representation of disease-free survival as a constant probability of experiencing an event also had another consequence. In the DES model it was possible to make the assumption that if patients had not experienced a relapse after 11 years in remission they were 'cured' and the next event of interest to the decision model was death from other causes. In the Markov process it was not possible to split the destination of patients according to time spent in the state, so all patients leaving the state were subject to the same probabilities of experiencing a more severe relapse, or progressing straight to death from other causes.

To demonstrate the impact of the different approaches to the representation of remission following a locoregional relapse the Markov process was analysed using the median DFS and the estimated mean DFS. The respective outputs give an indication of the potential importance of this shortcoming of Markov processes.

Metastases

From remission, patients could experience metastases or die from other causes. Patients in the metastatic states could only progress to death from the disease. The data identified in the literature describing survival from metastases were presented as set survival times, rather than data describing the probability of experiencing an event in a particular interval. The DES model incorporated such data in exactly the format that the data were available: for each sampled survival time, every patient experiencing a form of metastases remained in that health state for the sampled survival period.

The Markov process required the conversion of set survival times to constant probabilities of experiencing death at any point following the diagnosis of metastases. The following formula was employed to transform set survival times to constant probabilities:

$$\text{pr(event)} = 1 - \exp\left(\frac{-1}{x}\right)$$

where x is the set survival time.

Further sub-analysis of the impact of the specific differences between the two models was undertaken using a separate Excel spreadsheet model to estimate the outputs associated with varying lengths of survival. Set survival times of between 1 and 40 months were used to accommodate the upper range of the survival estimates for metastases. Monthly costs of £469 (the mean monthly cost of bone metastases [8]) were discounted at a rate of 6%, whilst quality adjusted survival (using a utility weight of 0.5) was discounted at 1.5% [19]. Unadjusted survival was not discounted.

The breast cancer models covered a time horizon of 50 years, which is the maximum that the constant probabilities may be applied to patients remaining in a metastatic state. The macro also linked the length of follow-up in the assumed metastatic state to the start year in the state. For example, if the start year in the state is sampled as year 10 then the outputs from the state are summed for the following 40 years in the state. Start years of between 0 and 26 years were tested. This set-up provided the most accurate portrayal of the effect of converting set survival times to constant probabilities.

Populating the models

Separate reviews of the literature were undertaken for five components of the decision model – adjuvant therapies, treatment toxicity, timing of relapse or death with no evidence of cancer, types of relapse, and progression from relapse. Including all sources, at the time of the final analysis a total of 343 full papers or documents had been reviewed. Additional primary sources for some of the cost parameters were used due to the small amount of relevant data in the literature. Full details of the data used to populate the model are published in a separate paper [8].

For the stochastic analysis of the decision models, probability distributions were described to represent the identified data for each input parameter. Theoretical considerations were applied to the choice of probability distribution for different types of parameters. The process involved examining the characteristics of the different types of input parameters and assigning a particular type of probability distribution with properties that matched the input parameters. The distribution parameters for each probability distribution were informed by the available data for each input parameter. Four categories of parameters were identified – proportions, survival times (length of time to next event), costs and utility values and an

appropriate probability distribution chosen for each category:

1. Proportions describe the probability that a patient will experience an event, which is bounded by 0 and 1. Employing Bayesian methods for specifying prior distributions the beta distribution provides the most realistic representation of proportions [20];
2. Survival times describe the length of survival (or time to next event), they are bounded by 0. The gamma distribution is bounded by zero and approximates the normal distribution at large samples. It is also extremely flexible, using a shape parameter to describe the available data accurately [19];
3. Cost parameters have been described by the lognormal distribution [15,21,22], though the gamma distribution may provide a more flexible description of the sampling distribution of costs.
4. Utility values possess similar properties to proportions.

The method of moments specifies formulae for estimating parameters for the chosen probability distributions by finding expressions for them in their lowest order moments, then substituting sample moments into the expression [19]. The data identified from the literature review were combined with these formulae to estimate relevant parameters for the chosen probability distributions.

Running the models

A deterministic Markov process can be built using a spreadsheet package alone, but Crystal Ball uses second-order Monte Carlo simulation to analyse the model stochastically by randomly sampling sets of input parameters from probability distributions, analysing each iteration using the cohort-based method.

DES employs first-order Monte Carlo simulation to describe the individual experiences of patients for each set of input parameter values, from which only the mean output values are of interest. It was necessary to establish an adequately 'large' number of patients to be run through the first-order Monte Carlo simulations to be sure that the mean output values were as close as possible to the true mean value for each parameter set. To test the adequacy of alternative sample sizes the input parameter values were held constant at their mean values. Repeated replications of the model were undertaken using different random number seeds for each replication of the same sample size. The use of alternative random numbers means that patients within alternative replications sample different values from probability distributions within the model, but the mean values of the model outputs *should* remain the same. Sample sizes of 100, 1000 and 10 000 were tested. For each sample size the DES model was run 50 times, each run starting from a different random number seed.

The results of the analyses are presented in a cost-effectiveness plane in Figure 2. The plots show a very wide dispersion of estimates derived from runs of 100 patients, whilst the level of variation remained large when 1000 patients were run through the model for each set of parameter values. A much tighter concentration of estimates is observed for the runs informed by 10 000 patients with the difference in costs varying between around £1000 and £1250 and the effects difference falling between 0.5 and 1 QALY. Although larger samples would reduce the observed random error further, runs of 10 000 patients provided the best trade-off between accuracy and the running time of the DES model.

Results

The final analysis of the two models was undertaken on 700 MHz PC with a Pentium II processor and took around 1 h and 3 days for the Markov process and DES model, respectively. However, the time to analyse not only includes the final 'correct' experimentation with the models, but the whole process of verification and validation, which required significantly more time than the final experimentation phase (weeks in the case of the DES model, days for the Markov process).

The aggregate values for each of the model outputs derived from the two modelling techniques are presented in Table 2. The mean costs, QALYs, and life years estimates do vary between the two modelling techniques, but in the same direction, ie. all three outputs are higher in the DES model. The cost differences are under £500 for both therapy options, and the differences in the QALY estimates

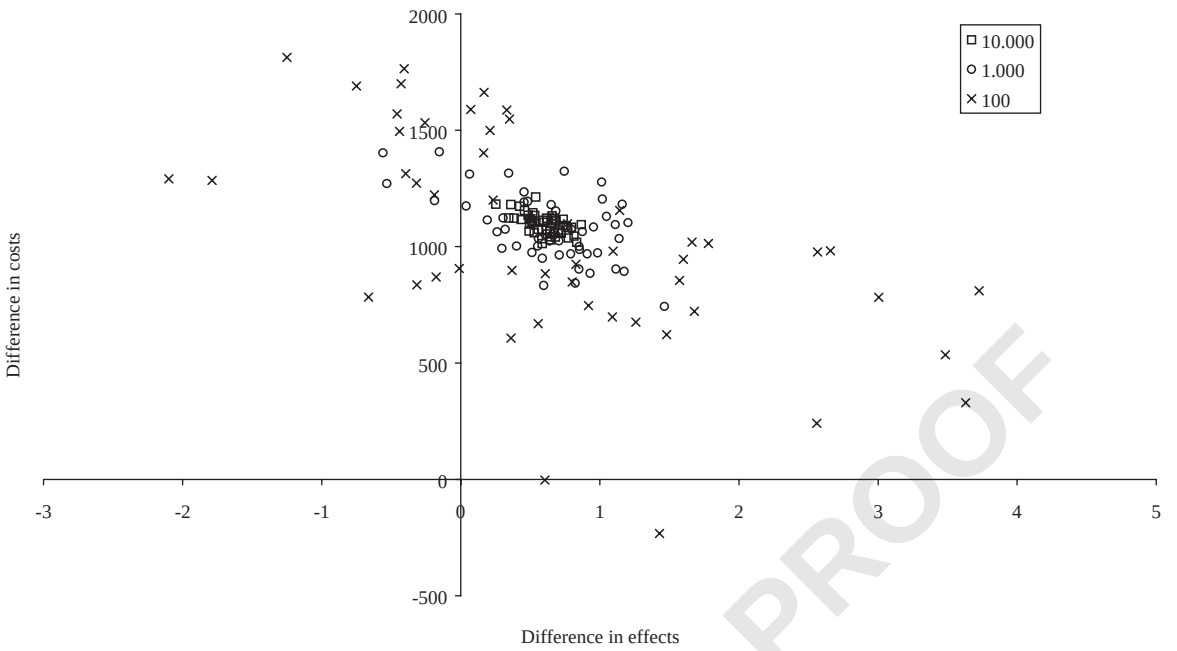

Figure 2. Cost-effectiveness plane illustrating the accuracy of alternative run sizes for the analysis of the DES model

Table 2. Comparison of the model outputs from the Markov process and DES model.

	Costs		QALYs		Lifeyears	
	DES model	Markov process	DES model	Markov process	DES model	Markov process
Tamoxifen and chemotherapy	£9146	£8740	12.14	12.00	16.01	15.74
Tamoxifen alone	£7115	£6721	11.56	11.40	15.16	14.86
	Mean ICER		2.5th percentile		95th percentile	
DES model	£3483		£452		Tamoxifen dominates	
Markov process	£3365		£588		Tamoxifen dominates	

are under 0.15 QALYs. These results lead to a very small divergence in the incremental cost-effectiveness ratios (ICERs) reported by the two models. Relevant percentiles derived from the output distributions of ICERs from the two models are presented in Table 2, and are also similar. Neither of the 2.5th percentiles exceeds £600, whilst even at the 95th percentile tamoxifen remains dominant on the basis of the intervals reported by both models.

The cost-effectiveness acceptability (CEAc) curve provides a more flexible interpretation of cost-effectiveness presenting the probability that an intervention is cost-effective for all potential values of an additional unit of effect [23]. The CEAc curves presented in Figure 3 show that the Markov process reports a slightly higher probability of tamoxifen and chemotherapy producing positive net benefits for all values of an additional QALY than the DES model.

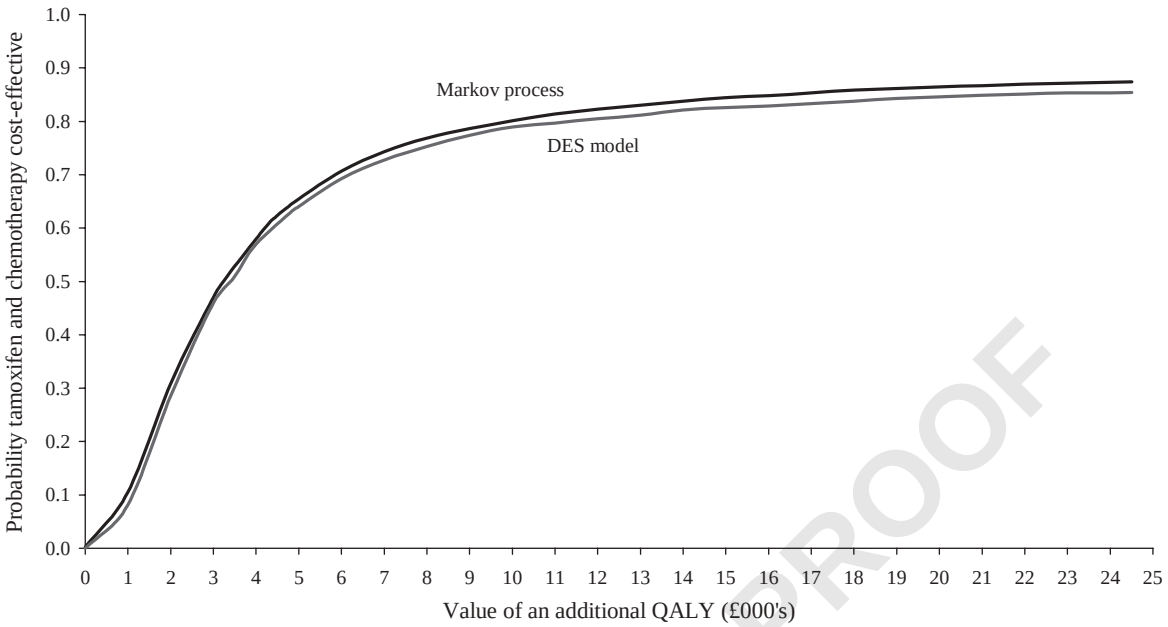

Figure 3. Cost-effectiveness acceptability curves derived using alternative modelling techniques

The closeness of the results produced by the Markov process and the DES model disguises some potentially important differences within the models that appear to have balanced each other out. The main area of divergence concerned the representation of survival from diagnosis with metastases, which were described in their available format in the DES model (as set survival times), but which required transformation to constant transition probabilities in the Markov process. A separate Excel model was developed to compare the outputs from the two models from a single metastatic state under a range of data assumptions. Table 3 shows that the differences, especially in costs (which were subject to the highest discount rate), can be substantial. Indeed, in the case where the sampled survival period is 40 months and patients enter the state at a younger age the cost difference between the models is £3750. The maximum QALY difference, for this one state within the model, was estimated to be 1.34, whilst the largest difference in life years gained was around 1.7 months.

Discussion

In the case study evaluation reported in this paper, the comparison of the alternative modelling techniques identified two areas (the use of state entry-dependent probabilities and set survival times) in which DES facilitated a more flexible representation of the available data than the Markov process, though the respective outputs were similar. The closeness of the results suggests that it is unlikely that the use of one model's results over the other would lead to an alternative resource allocation decision. Indeed, it may be concluded that the slight benefits of DES, in terms of increased flexibility, were outweighed by the far greater time required to develop and evaluate the DES model.

In the absence of discounting and the use of attributes the building of a DES model would not be significantly more complex than a Markov process. The development of the case study DES model was relatively complex because it covered a long time horizon and incorporated the use of patient attributes, which required the use of programming code, albeit relatively simple code. An example of the increased complexity of the DES model is in relation to the process of validation, which used data that described the model's outputs at specific time points (such as 4 and 10 years). To collect data constrained by time it was necessary to run the full DES model, but collect data at the end of each state up to the end of the specified time period. This was only possible

Table 3. Examples of the discounting effect on differences between the DES model and the Markov process

Set survival time	Start year	DES data	Markov data	Difference	Difference (%)
Costs					
1	1	£442.45	£478.72	−£36.27	−8.20%
1	25	£115.83	£125.33	−£9.50	−8.20%
40	1	£16529.68	£12778.77	£3750.91	22.69%
40	25	£4327.43	£3342.34	£985.08	22.76%
QALYs					
1	1	0.49	0.53	−0.04	−8.20%
1	24	0.35	0.38	−0.03	−8.20%
40	1	19.36	18.02	1.34	6.91%
40	24	13.74	12.76	0.98	7.15%
Life years					
1	1	1.00	1.08	−0.08	−8.20
1	24	1.00	1.08	−0.08	−8.20
40	1	40.00	40.00	0.00	0.00
40	24	40.00	39.86	0.14	0.36

by inserting programming code that effectively asked if the patient had been in the model for the specified period at regular intervals when aggregating the costs and effects at the point of exit of each state. In effect, this aspect of the validation process was subject to a separate process of verification. In the Markov process, it was simply a case of aggregating the model's outputs to the end of the relevant cycle.

The time inputs required to build the model will obviously vary according to factors such as experience, ability and other commitments, and these factors should be accounted for in estimating the time required to build a model. Such factors will also affect the time required to verify and validate a model, which often takes the largest proportion of the whole model development and experimentation phase of a modelling evaluation. Another factor influencing the running time for the DES model is the necessary number of patients within each first-order analysis of the model. In simpler models, with less variation within the model, the smaller number of patients required will reduce running time considerably.

The empirical comparison of the two modelling techniques illustrates that the increased flexibility of DES may only provide significant improvements in the accuracy of a modelling evaluation when the areas of increased flexibility apply to a large proportion of the model.

State-entry dependent probabilities refer to data that describe patients' duration in a health state (other than a start state) in the format of a survival curve for which a proportion of patients remain alive (or disease free) at the end of the follow-up period. In the case study evaluation this situation arose around the representation of remission following the experience of a locoregional relapse. The DES model noted the age and time at entry to the state of each patient as they entered the health state so that individual transition probabilities could be applied to each patient to represent each successive time period. A similar representation of the data in the Markov process would have required the specification of 132 repeat states. Such a representation may be more feasible in Markov process built using a programming language, but the necessary expansion of the model in software such as Excel spreadsheets or specialist Markov model software (such as DATA by Treeage) would create very large and impractical models. The use of repeat states would have been more feasible if annual rather than monthly model cycles were employed, but the choice of cycle length was chosen for clinical relevance.

The use of look-up tables was also considered as a solution to the representation of state-entry dependent probabilities in the Markov process. However, any such solution to this area of the model would require first-order analysis of the Markov process and such adaptations to the Markov process that it would begin to resemble a DES model.

The handling of state-entry dependent probabilities in the DES model meant that more intuitive assumptions, which accounted for each patient's age, could be applied to the portion of the survival curve that remained at the end of the follow-up period. However, for this aspect of increased flexibility to have a major impact on the model's outputs it would be necessary for a larger proportion of the model's states to be informed by state-entry dependent probabilities. A larger impact would also be expected if the relevant 'survival curve' data populating the model included a large proportion of censored patients, and if patient pathways from the relevant states varied according to the time spent in the states.

Issues around the format of the available data are mainly applicable to modelling studies that employ secondary clinical data. In such circumstances the analyst is bound by the presentational norms for particular types of data. The process of modelling adjuvant therapies for breast cancer highlighted this issue in the representation of survival from diagnosis with metastases, where the data were available in the format of set survival times. The results of the sub-analysis investigating this issue showed that the conversion of such data to transition probabilities, as required for the Markov process, has the potential to underestimate the true impact of the input data. However, this factor had only a small impact on the results from the Markov process reported in this paper, and it is likely that this issue would only cause significant underestimates in models that covered long time horizons for which the majority of the input data described set survival times.

Conclusions

The outputs derived from the alternative modelling techniques were sufficiently close to conclude that, given the substantially increased analytic inputs required for the DES model, a Markov process would have been the optimal technique for the reported evaluation of alternative adjuvant therapies for early breast cancer. There may be circumstances in which a DES model will provide a more accurate representation of the available data, though the results of the reported empirical comparison of the two techniques indicate that quite specific model characteristics will be required. In some cases, the perceived increased accuracy of DES may provide the informed user of the evaluation's results with more confidence in the validity of the model and it's outputs.

The purpose of this paper has been to draw out the differences between the use of a Markov process and a DES model for the chosen case study, and to present generalisable definitions of the differences that can be applied and interpreted in the context of other treatment areas. The relative importance of each of the differential factors identified is likely to vary between treatment areas, but on the basis of the work presented in this paper analysts should be able to make an informed choice with respect to the relative advantages of the alternative decision modelling techniques in other treatment areas.

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