Mathematical programming for the optimal allocation of health care resources

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Abstract

The standard decision rules of cost-effectiveness analysis either require the decision maker to set a threshold willingness to pay for additional health care or to set an overall fixed budget. In practice, neither are generally taken, but instead an arbitrary decision rule is followed which may not be consistent with the overall budget, lead to an allocation of resources which is less than optimal, and is unable to identify the programme which should be displaced at the margin. We show, using a policy-relevant example, how mathematical programming can be used as a generalisation of the standard decision rules. This approach allows us to incorporate important aspects of the decision into our framework that are not available if decision making is made using threshold values of the incremental cost-effectiveness ratio alone. We are able to examine alternative budgetary rules about when expenditure can be incurred, and show the opportunity loss, in terms of health benefit forgone, of each budgetary rule. We show that indivisibility in a patient population and other equity concerns can be represented as constraints in the programme and we estimate the opportunity loss if these concerns are held for some patient populations, and for all patient populations.

Keywords

Cost-effectiveness analysis; cost-benefit analysis; mathematical programming, resource allocation

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Introduction

The standard decision rules of cost effectiveness analysis allow two alternative methods of determining the efficient allocation of healthcare resources in the absence of a market, assuming constant returns to scale, independent treatment options and perfect divisibility [1-3]. Firstly, the decision maker can set a threshold willingness to pay for additional health benefits and implement all independent treatments with positive net benefit. In these circumstances the budget for healthcare is not fixed but implicitly determined. Secondly, the decision maker can set a budget for healthcare and select from all available treatments the subset that maximises health benefits subject to the budget constraint. Here the shadow price of the budget constraint can be interpreted as the reciprocal of the implied threshold willingness to pay for additional health care benefits.

In practice, neither of these approaches is generally taken, but instead an arbitrary decision rule is followed. The decision maker chooses a threshold willingness to pay which may not be consistent with the existence of an overall fixed budget for healthcare [4]. Under these circumstances, implementing a new intervention will displace another programme at the margin but the latter is usually not identified by the decision maker or the analyst. Without solving the allocation problem as a whole, an arbitrary method will lead to a sub-optimal allocation of resources and does not identify the true opportunity cost of the decision [5].

Stinnett and Paltiel showed how mathematical programming (MP) can be used to solve the allocation problem and also used to accommodate more complex information regarding returns to scale, indivisibilities and ethical constraints including the cost of equity [3]. Some authors have developed theoretical aspects of this approach in the context of health economics, considering issues such as variable returns to scale [6], indivisibilities [7 ,8] and uncertainty of costs and effects [9]. To date, there have only been a few applications to policy problems. Some studies have applied MP techniques to allocate resources within specific patient groups and healthcare programmes [10-12]. Other authors have aimed to solve the allocation problem as a whole for healthcare organisations with a fixed budget. Wang evaluated a hypothetical allocation problem to maximise life years gained for the population of a US Managed Care Organisation, while Cromwell evaluated the mix of hospital services in an Australian Area Health Service [13 ,14]. Both studies were limited by only considering costs incurred in the first year of treatment.

The purpose of this study is to formulate a mathematical programme to allocate resources within and between healthcare programmes. We apply the mathematical framework to a stylised but relevant policy problem using real data. We show how to solve the allocation problem to take account both of the long term costs of each treatment option and the constraints of various short-term budget rules. We demonstrate using our dataset how indivisibilities and equity concerns can be represented as constraints, following the method of Stinnett and Paltiel and that the opportunity cost of equity concerns varies between patient groups [3].

The paper is structured as follows. First we provide the rationale for the formulation of the allocation problem, and provide the solution for the basic allocation problem. We then consider how the solution would change if there are constraints on when expenditure can be incurred as well as the overall budget. We relax the assumption of perfect divisibility in selected patient groups and then for all patient groups, and show how other equity concerns can also be represented as constraints.

The formulation of the allocation problem

Our basic formulation of the problem is as follows. The objective is to determine the optimal values of the available healthcare treatments (x_{ijk}) so as to maximise the gross benefit B subject to an overall budgetary constraint δ, and constraints that ensure all members of each independent healthcare programme $k := 1 \ldots K$ and population group $i := 1 \ldots I_k$ receive one and only one treatment $j := 1 \ldots J_k$, that is:

The variable varies between zero and unity ( ) where means

that no proportion of population group i is allocated treatment j in healthcare programme k, and $x_{ijk} = 1$ means that all members of population group i are allocated treatment j in healthcare programme k.

The time horizon (T) is the total time over which costs and benefits arising from the available treatments are evaluated. The model presented here is static; that is, the proportion of the population selected now for each treatment will not change over time. The review period is denoted by τ ; that is, we assume that the same treatment decision will also be applied to patients who are newly diagnosed during the next τ years and their costs are also taken into account. After τ years it is assumed the decision will be reviewed and the costs of no further incident patients are considered. The time index variable is t, where $t = 1 \ldots T$. Denote also by $c_{ijk}(t)$ the incremental cost at year t of treatment j in healthcare programme k if the treatment is given to all members of population group i ; that is, both the pre-existing and newly diagnosed patient population. The cost $c_{ijk}(t)$ of each treatment j ($j > 1$) in year t is relative to a comparator treatment ($j = 1$) for which costs are defined to be zero. The comparator is usually current care. The total incremental cost in year t of all healthcare programmes (relative to current care) across all treatments is therefore given by

$$C(t) = \sum_{k=1}^{K} \sum_{j=1}^{J_k} \sum_{i=1}^{I_k} x_{ijk}\, c_{ijk}(t) \qquad t = 1..T$$

(2)

For benefits, it is assumed that the cumulative incremental quality adjusted life years (QALYs) – relative to the comparator treatment – are known only over the time horizon of the model and these are denoted by b_{ijk} where b_{ijk} is the gross benefit of treatment j in healthcare programme k if the treatment is applied to all members of population group i . The total incremental benefit relative to current care is therefore

$$B = \sum_{k=1}^{K} \sum_{j=1}^{J_k} \sum_{i=1}^{I_k} b_{ijk} \; x_{ijk}$$

(3)

This formulation of the problem assumes both costs and benefits show constant returns to scale. The coefficients b_{ijk} are discounted to allow for time preference.

Problem (1) is a Linear Programming (LP) problem. The linear programme is solved using the *Mathematica Version 5* built-in LP solver "DualLinearProgramming" [15]. This returns the optimal values of the decision variables and the shadow prices of the constraints.

A policy example

The approach taken in this paper recognises certain important features of the policy problem. Resources are allocated in a publicly-funded system by planning mechanisms. Ideally, all treatments for all population groups in all healthcare programmes would be compared against one another to maximise overall health benefits, subject to budget, equity and other constraints. This is unlikely to be feasible. A more limited but relevant policy problem is suggested, in the context of the UK health system, by the recognition that funding should be made available to National Health Service (NHS) bodies in order to implement the recommendations made by the National Institute for Health and Clinical Excellence (NICE). NICE currently undertakes technology appraisals, in which the independent appraisal committee makes recommendations about a set of healthcare technologies, which take into account the cost of additional QALYs by calculating the incremental cost effectiveness ratio. The threshold of willingness to pay for additional health benefits is not precisely defined but is usually in the range £20000 to £40000 [16]. Maynard (2004) recommends that NICE receives an annual, ‘top-sliced’ budget and is required to fund all advice within that expenditure envelope [17]. The consequence of such a policy would be that it would no longer be efficient for NICE to make recommendations for each appraisal in isolation from the others. In order to ensure that its recommendations were affordable within the overall financial envelope, all options would have to be compared against one another in a mathematical programme.

To explore how this might work, three healthcare programmes have been identified from the 6th and 7th wave of appraisals considered by NICE that were published between 2002 and 2003 [18]. The healthcare programmes included in this study, their prevalent and incident populations, and the treatments which were evaluated in the assessment reports are shown in Table 1. The dimensions of the LP problem (1) corresponding to this policy example (Table 1) are: $K = 3, I_1 = 4, I_2 = 2, I_3 = 2, J_1 = 4, J_2 = 2, J_3 = 2$. The healthcare programmes are evaluated over 15 years (i.e. $T = 15$) and the revision time of decisions is assumed to be 5 years (i.e. $\tau = 5$). We estimate the coefficients for incremental benefits b_{ijk} and costs $c_{ijk}(t)$ from the information provided by the assessment reports.

Solution of allocation problem

Table 2 shows the optimum level of implementation of treatments for each healthcare programme and population groups at budgets of £20m, £50m, £180m and £240m. In linear allocation problems where there is a single budget constraint, there will always be at most one independent programme that will offer mixed treatments and all the other treatments in all the other programmes will be pure; that is, one treatment will be implemented in full and the other options are not offered at all. The level of implementation of the each treatment, and whether an intervention is mixed or pure, changes with the budget. This solution is identical to that obtained by following the standard decision rules set out by Johannesson and Weinstein [1].

We can show how the budget constraint, the shadow price and the threshold cost per QALY are related in the basic allocation problem (Figure 1). The shadow price is the gain in QALYs if the budget were to grow by £1m. The reciprocal of the shadow price is proportional to the threshold willingness to pay for additional QALYs.   The shadow price falls (or the threshold willingness to pay increases) with the size of the budget. In this example, at a budget of £338m, all the most effective treatments in all patient groups are funded in full and further budget will have no additional health benefits. Figure 1 shows that the shadow price follows a characteristic step (i.e. piecewise-constant) function. If an additional £1m budget expands the feasible solution region without changing its basic shape, so that the same set of optimal treatments are selected as before but with different levels of implementation, then the shadow price (the additional QALYs per additional £1m) will remain constant. If the additional £1m changes the optimal solution so that a treatment which was previously implemented partially is now dropped entirely, then the shape of the feasible solution region will change and the shadow price will be lower than before.   When the budget reaches the point at which all the most effective treatments for each population group are funded in full, additional funding will not achieve any additional benefits and so the shadow price will be zero. If the budget is exogenously defined, then the threshold maximum willingness to pay for additional health benefits is a positive not normative question.

Evaluating alternative budget rules

Problem (1) imposes no constraints about when the budget can be spent, and the solution shows us the optimal allocation of resources over time. Conventional methods of cost-effectiveness analysis assume that the decision maker has complete flexibility about when the budget can be spent. However, a budget in the context of the NHS is usually a sum of money allocated for a particular purpose for a given period of time, usually one year. If we have constraints on when the budget can be spent as well as its total size, then the timing of expenditure for each treatment is important over and above discounting. Decision making using incremental cost-effectiveness ratios (ICERs) alone cannot handle more than one constraint and therefore cannot deal with this.

It is possible to explore alternative budget rules. Firstly, we consider the case where the total allocation δ is divided into equally sized maximum annual budgets over the time horizon of the analysis, that is, 15 years. The cost constraint in LP problem (1) is amended so that we now have 15 budget constraints, one for each year, as shown by Eqn (4)

$$C(t) \le \delta / 15 \qquad t = 1 \ldots T \tag{4}$$

Secondly, we consider the case where the total allocation has to be spent within the first 5 years. The budget rule is given by Eqn (5). In this formulation, treatments that have a cost beyond 5 years are permitted only if their costs are offset by other programmes which are cost saving in these time periods. There are now 10 budget constraints – one for the first five years and a further 9 for each of years 6 to 15.

$$\sum_{t=1}^{5} C(t) = \delta$$
$$C(t) = 0 \qquad t = 6 \ldots 15$$

(5)

Table 3 shows the health gain achieved at an (arbitrarily chosen) budget of £180m with no equity constraints under alternative budget rules. Under these alternative rules, not all the budget will be spent and there will be an opportunity loss compared with the basic solution. Figure 2 shows the variation of health gains (QALYs) for each of the budget allocation rules at different values of the overall budget. At values of the total budget less than £75million, the basic formulation and the formulation where the total allocation has to be spent within 5 years give the same solution, indicating that up to this budget these additional constraints are non-binding. However, as the total budget increases, the restrictions become binding and lead to an opportunity loss.

The decision making algorithms using ICERs are unable to handle the case where there are alternative budgetary rules. The mathematical programme is able to incorporate these rules as additional constraints. It is possible to incorporate other resource constraints; for example, rules restricting expenditure on specific budgets such as pharmaceuticals or capacity constraints for specialist personnel or facilities.

Indivisibility and horizontal equity

In Problem (1), the decision variables are permitted to take fractional values. This is the assumption of perfect divisibility. Only a proportion of the population would be allocated to receive each of the treatments under consideration (although all members of the population would receive some treatment). This might be thought of as the 'efficient' solution in the absence of any equity concerns. Its implementation, were it possible, would require some arbitrary allocation mechanism, such as first-come first-served. This might be considered inequitable since the members of the population are assumed to all be of equal need [3].

We can relax the assumption of perfect divisibility for some or all patient populations. A requirement that equity considerations should be incorporated can be thought of as imposing additional constraints on the mathematical programme. The 'horizontal equity' consideration that people with equal need should receive equal access to treatment imposes the constraint that the decision variables are binary for some population group i and healthcare programme k (Eqn. (6)).

$$x_{ijk} \in (0,1) \qquad i = 1 \ldots I_k, j = 1 \ldots J_k, k = 1 \ldots K \tag{6}$$

For example, we might require that all patients with type 1 diabetes are treated in the same way (i.e. are indivisible), or that patients aged less than 60 years with non-Hodgkins lymphoma are treated in the same way, or that all patient populations are indivisible.

Horizontal equity concerns (Problem (1) with the additional constraint Eqn (6) imposed on one or more population groups) are a 0-1 Mixed Integer Linear Program (0-1 MILP). Problems of this type can be difficult to solve. In this paper, we use a computationally-intensive method of constraining the selected treatment options to take values of 0 or 1, evaluating the linear programme for each possible permutation, and choosing the permutation that maximises the objective function. This method is only feasible when a very limited number of decision variables take binary values. Further work will focus on efficient methods to solve MILP problems [19-21].

Table 4 shows the opportunity loss if indivisibility is imposed separately in two patient populations, and if indivisibility is required in all populations. The base case for this comparison is chosen as the "equally phased" budget for illustrative purposes because, in the basic mathematical programme, the equity constraints would not be binding if we imposed them on more than one population. In the large population with type 1 diabetes, the opportunity loss is 520 QALYs. The effect (compared with the base case) is to decrease the health of the type 1 diabetes population, who now all receive the less effective treatment where previously only a proportion would have done, but to increase health in other populations more of whom now receive more effective treatments. The requirement for indivisibility only in the small population aged less than 60 with non-Hodgkins lymphoma costs 19 QALYs. The requirement for horizontal equity in all populations does not impose further opportunity loss because, in this example, the other constraints are not binding once the indivisibility has been imposed in the population with type 1 diabetes.

Further equity constraints

Further equity considerations can be incorporated into the mathematical programme. Any characteristic which is known to affect cost, quality of life or survival could be used to differentiate patients with respect to the treatments they are offered. It may not be considered equitable to allow different access to treatment if patients are similar in some respects but differ in others. For example, in some cases it may be acceptable to differentiate between patient groups on the basis of age. However, other characteristics may be more controversial such as gender or social class. This can be expressed as the requirement that patients within the same health care programme have the same probability of receiving a given treatment, regardless of other characteristics. The examples available in this stylised scenario are rather artificial, but are used to illustrate the issue. For example, it may be considered unfair to use patients' age to differentiate with respect to the treatment offered for lymphoma (which can be written as a constraint in the form $x_{122} = x_{222}$), or unfair to allow patients with type 1 and type 2 diabetes different probabilities of receiving the more effective long acting insulin treatment (written as a constraint in the form $x_{123} = x_{223}$). These concerns can be written as equity constraints which can be imposed either separately or together, or conceivably together with indivisibilities.

Table 5 shows the results of an equity concern that it is unfair to use particular characteristics to differentiate with respect to the treatment offered, firstly for access to rituximab for non-Hodgkins lymphoma and, secondly, for access to long acting insulins for diabetics. As before, the opportunity loss of holding these equity concerns is not the same for all healthcare programmes. There is an additional opportunity loss if we wish to hold these equity constraints in both populations.

The formulation of equity concerns as constraints on a mathematical programme allows us to evaluate their opportunity cost in terms of QALYs forgone, compared to the scenario where there are no equity constraints. Furthermore, we can evaluate the opportunity cost of equity separately for each patient population. In principle, this might be used to describe the choices and trade-offs available to decision makers between efficiency and equity, including the opportunity cost of having the same equity concerns for all patient populations.

Discussion

In this paper, we have used mathematical programming to allocate limited healthcare resources for treatments between and within a set of patient populations. Johannesson and Weinstein showed that, if one was to implicitly accept the resulting level of expenditure as the budget, decision making using a threshold willingness to pay is equivalent to the basic LP problem set out in this paper as Problem (1) [1]. Stinnett and Paltiel argued that mathematical programming techniques allowed the incorporation of more complex information and additional constraints [3]. This paper adds to this work by showing that the profile of costs over time may be important and that it is possible to evaluate alternative budgetary rules. We are also able to incorporate indivisibility and other equity concerns as constraints and find that different equity concerns have different implications for efficiency, and that the effect will vary from patient population to population. It is not possible to use a threshold willingness to pay to make decisions where there are constraints additional to an overall budget constraint. We have shown that mathematical programming to assist priority setting is feasible in a context where there is a finite number of clear alternative options and a fixed budget. One such context may be the decisions made each year by an agency such as NICE, and we have demonstrated an application using published or publicly available information.

Our application of mathematical programming to a policy-relevant decision has revealed several methodological challenges that should be addressed if these techniques are to progress. We discuss two of these. Firstly, we have made some attempt to incorporate the effects of time in to the analytic framework. We have included annual budget constraints because we believe these constraints may be an important feature of the decision problem. We have also considered not just the current prevalent population but future incident patients, up to a review date of five years. However, this review date has been arbitrarily chosen for convenience. An alternative approach might be suggested by multistage or dynamic programming, in which allocation decisions can change over time [22]

Secondly, the parameters of the model are not known with certainty. There is uncertainty in the costs and benefits per patient, and the epidemiological parameters of current prevalence and future incidence, and in the budget constraints. A probabilistic approach to handling uncertainty would need to incorporate the coefficients of the model as random variables with *a priori* specified probability distributions, preferably including the correlations between them (particularly between costs and effects). The formulation of the problem as a stochastic mathematical programme, where the coefficients are random variables, has been proposed [9]. The solution to this type of stochastic problem is unlikely to be the same as that for the deterministic case even when the coefficients take their expected values. More importantly stochastic analysis would allow decision makers to consider the value of conducting research to inform the allocation problem as a whole [23 ,24]. In this sense, it provides a framework where the value of information about a particular technology or particular parameters can be considered in the context of the system-wide allocation problem.

We have shown that the use of an arbitrary threshold willingness to pay does not identify the correct opportunity cost of the decision and will, therefore, lead to a sub-optimal allocation of resources. Johannesson and Weinstein have argued that decisions are usually made at the margins of implicit budgets and, therefore, a MP (or budget-constrained) approach is unrealistic and unnecessary [1]. However, we know that even the healthcare systems of large, developed economies such as the UK are subject to annual budget constraints. Currently, NICE makes recommendations about new treatments without considering which programmes are to be displaced and this causes confusion and delay among those who are required to implement the decisions. Although a number of methodological challenges still need to be addressed, mathematical programming offers a transparent and coherent decision making framework to identify opportunity cost, account for annual budgets and show the opportunity costs of different equity concerns.

References

1. Johannesson M, Weinstein M. On the decision rules of cost-effectiveness analysis. *Journal of Health Economics* 1993;12:459-467.

2. Birch S, Gafni A. Economics and the evaluation of health care programmes: generalisability of methods and implications for generalisability of results. *Health Policy* 2003;64(2):207-219.

3. Stinnett AA, Paltiel AD. Mathematical programming for the efficient allocation of health care resources. *Journal of Health Economics* 1996;15(5):641-653.

4. Rawlins M, Culyer A. National Institute for Clinical Excellence and its value judgements. *BMJ* 2004;329:224-227.

5. Birch S, Gafni A. The NICE approach to technology assessment: an economics perspective. *Health Care Management Science* 2004;7:35-41.

6. Elbasha EH, Messonnier ML. Cost-effectiveness analysis and health care resource allocation: decision rules under variable returns to scale. *Health Economics* 2004;13(1):21-35.

7. Earnshaw SR, Dennett SL. Integer/linear mathematical programming models - A tool for allocating healthcare resources. *Pharmacoeconomics* 2003;21(12):839-851.

8. Sendi P, Al MJ. Revisiting the decision rule of cost-effectiveness analysis under certainty and uncertainty. *Social Science & Medicine* 2003;57(6):969-974.

9. Sendi P, Al MJ, Gafni A, Birch S. Optimizing a portfolio of health care programs in the presence of uncertainty and constrained resources. *Social Science & Medicine* 2003;57(11):2207-2215.

10. Earnshaw SR, Richter A, Sorensen SW, Hoerger TJ, Hicks KA, Engelgau M, et al. Optimal allocation of resources across four interventions for type 2 diabetes. *Medical Decision Making* 2002;22(5):S80-S91.

11. Zaric GS, Brandeau ML. Optimal investment in a portfolio of HIV prevention programs. *Medical Decision Making* 2001;21(5):391-408.

12. Brandeau ML, Zaric GS, Richter A. Resource allocation for control of infectious diseases in multiple independent populations: beyond cost-effectiveness analysis. *Journal of Health Economics* 2003;22(4):575-598.

13. Wang LY, Haddix AC, Teutsch SM, Caldwell B. The role of resource allocation models in selecting clinical preventive services. *American Journal of Managed Care* 1999;5(4):445-454.

14. Cromwell DA, Viney R, Halsall J, Hindle D. Linking measures of health gain to explicit priority setting by an area health service in Australia. *Social Science & Medicine* 1998;47(12):2067-2074.

15. Wolfram S. *The Mathematica Book, Fifth Edition*. 5 ed. Champaign IL: Wolfram Media/ Cambridge University Press, 2003.

16. Devlin N, Parkin D. Does NICE have a cost-effectiveness threshold and what other factors influence it? A binary choice analysis. *Health Economics* 2004;13:437-452.

17. Maynard A, Bloor K, Freemantle N. Challenges for the National Institute for Clinical Excellence. *BMJ* 2004;329:227-229.

18. NICE. http:\\www.nice.org.uk, 2004.

19. Nemhauser GL WL. *Integer and combinatorial optimization*: John Wiley, 1999.

20. Koppe M, Weismantel R. An algorithm for mixed integer optimization. *Mathematical Programming, Series B* 2003;98:281-307.

21. Richard JPP, de Farias IR, Nemhauser GL. Lifted inequalities for 0-1 mixed integer programming: Basic theory and algorithms. *Mathematical Programming, Series B* 2003;98:89-113.

22. van Zon AH, Kommer GJ. Patient Flows and Optimal Health-Care Resource Allocation at the Macro-level: A Dynamic Linear Programming Approach. *Health Care Management Science. May* 1999;2(2):87-96.

23. Claxton K. The irrelevance of inference: a decision-making approach to the stochastic evaluation of health care technologies. *Journal of Health Economics* 1999;18(3):341-364.

24. Ades AE, Lu G, Claxton K. Expected Value of Sample Information Calculations in Medical Decision Modeling. *Medical Decision Making* 2004;24:207-227.

Table 1: Programmes, treatments, populations and time horizon reported in the assessment reports for the sample of NICE technology appraisals.

Healthcare programme (k) and population groups (i)	*Population: Prevalent*	*Incident /yr*	*Treatments (j)*	*Time horizon of assessment report*
k=1: Influenza			Four treatments available	Less than 1 year
1. Adults	4.805m	4.805m	1. Current care (no medication)	
2. Elderly	1.075m	1.075m		
3. Residential	0.025m	0.025m	2. Amantadine	
elderly	4.047m	4.047m	3. Oseltamivir	
4. Children			4. Zanamivir	
k=2: Rituximab for non-Hodgkins lymphoma			Two treatments available	15 years
1. Over 60s	236	11	1. Current care (CHOP)	
2. Under 60s	1243	59	2. Rituximab+CHOP	
k=3: Long acting insulins for diabetes			Two treatments available	9 years
1. Type 1	117000	4056	1. Current care (NHP)	
2. Type 2	39000	2790	2. Insulin glargine	

* Current care is the current mix of services : 30% have hospital dialysis, 30% satellite and 40% home dialysis. Hospital dialysis is not considered as a treatment option since it is less effective and more costly than alternatives in every year. However, future analyses may consider switch costs which are not included here.

** Healthcare programmes are indexed with letter *k*, treatments with letter *j* and population groups with letter *i*.