Solving for Multiple Objectives: The Use of the Goal Programming Model to Evaluate Energy and Climate Policy Options

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ABSTRACT

A critical shortcoming of most standard economic analysis is that it tends to focus on a single objective — either to minimize cost, or to maximize profit, welfare, or consumer utility. But the evidence suggests that both individual consumers and businesses tend to juggle a variety of objectives or concerns as they choose their next investment or make their next purchase. Hence, standard theory tends to restrict the full set of possible choices that would increase consumer welfare across a variety of social, economic, and environmental objectives.

Unfortunately, the current generation of policy tools does not have a meaningful capacity to solve for multiple rather than single objectives. Yet, the need for multicriteria decision models grows as policy makers continue to wrestle with an increasingly complex set of issues in the evaluation of energy and climate policies. One analytical tool that might provide further insights, given multiple objectives, is known as "goal programming." This is an optimization technique that draws from the family of mathematical programming models. The goal programming technique allows policy makers to identify the mix of technology investments that best satisfies the multiple, often competing, goals that exist within a given social or economic setting. This paper explores how technology options might differ under a variety of environmental and economic objectives compared to a single objective solution. Among the multiple objectives to be evaluated are annualized costs, level of both carbon emissions and air pollutants, and net employment benefits.

Introduction

A critical shortcoming of most standard economic analysis and models is that they tend to focus on a single objective to be achieved — either to minimize cost, or to maximize profit, welfare, or consumer utility (Ackerman, 1999; Laitner, et al, 2000; and Howarth, 2000). But the evidence suggests that both individual consumers and businesses tend to juggle a variety of objectives or concerns as they choose their next investment or make their next purchase (Simon, 1997; DeCanio et al, 2000). Hence, standard theory tends to restrict the full set of possible choices that would increase consumer welfare across a variety of social, economic, and environmental objectives.

Unfortunately, the current generation of policy tools does not have a meaningful capacity to solve for multiple rather than single objectives. Yet, the need for multi criteria decision models grows as policy makers continue to wrestle with an increasingly complex set of issues in the evaluation of energy and climate policies. One analytical tool that might provide further insights, given the existence of multiple rather than single objectives, is known as "goal programming." This is an optimization technique adapted from the family of mathematical programming models (Lee, 1976). This paper begins an initial inquiry into how the GP concept might be adapted for use in climate mitigation assessments using electricity consumption in the commercial buildings sector as the focus of the discussion.

The Goal Programming Concept

The use of energy is not a goal in itself. Ideally, energy use should be managed in a way that promotes the wide variety of goals or purposes typically found within any society or economy. Such goals may range from expanding the employment base to minimizing environmental impacts. In pursuing these multiple objectives, however, there may be limitations on what strategies can be pursued. It is in this context that the goal programming technique is useful. There are multiple concerns, a variety of choices to be made or not made, and a set of constraints on the financial, human, and energy resources available to implement the eventual choices.

Goal programming (GP) is a mathematical model. Similar to the linear programming algorithm, it solves for the set of choices that best satisfies multiple goals from among a variety of alternatives that are all competing for a pool of limited resources.[1] It is different from linear programming in two ways, however. First, where linear programming tries to achieve a single goal — usually minimizing cost or maximizing returns — goal programming tries to achieve multiple goals. Second, the GP model is based upon the "satisficing" principle first outlined by Herbert Simon in the 1950s.[2] Simon and others suggested that better decisions could be made if emphasis were given to achieving minimum levels of satisfaction rather than maximizing a single objective. This differs from both linear programming and conventional economic choice models that seek to maximize (or minimize) a single objective.

When decisions are guided by the maximization principle, only one objective can be pursued. The other objectives, if any, usually are forgotten; or they are sacrificed in order to maximize the priority goal. The example in the table below illustrates this point.

Table 1. Illustration of the Maximization versus Satisficing Principle

Economic Impact	Technology A	Technology B
Required Investment	$1,000,000	$600,000
Tons of NOx Reductions	40	50
Total Jobs	25	15

To explain the difference between the "maximizing" and the "satisficing" principles, two technologies are compared. Technology "A" is shown to reduce NOx emissions by 40 tons and create 25 jobs; but it costs $1,000,000 to implement. Technology "B," on the other hand, creates only 15 jobs but reduces NOx emissions by 50 tons. It is also the cheaper of the two technologies, requiring an investment of only $600,000. If the problem were to maximize the reduction of pollutants, alternative B would be clearly the logical choice.

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1. For a more thorough discussion of the goal programming technique, see Taylor (1986), pp 268-285.

2. The development of Simon's influence in the decision sciences can be found in Lee (1976), pp 177-179.

By maximizing emission reductions through investments in technology B, employment gains appear to be sacrificed although at a smaller impact on the program budget. On the other hand, if the objective is to maximize employment or other economic activity, technology A would be the obvious choice.

Suppose, however, that all three goals would be "satisficed" if NOx emissions are reduced by 45 tons, at least 20 jobs are created, and spending is held to $800,000. With these minimum levels of satisfaction, all three objectives can be achieved. The solution, in this case, is to build an investment portfolio that includes both technologies — 50 percent of A and 50 percent of B.

The solution for the example shown above is easily demonstrated. When the problem involves four, five or more goals, and as few as four or five technology choices, the analysis becomes too complicated for a quick manual calculation. The use of goal programming software packages can facilitate the analysis. Thus, by blending traditional benefit-cost and other analytical tools with the GP technique, new insights can be obtained to some very tough problems.

Illustrating the GP Problem Structure

To better understand the value of the goals programming technique in energy policy analysis, let us assume that a municipal utility is interested in reducing both its own costs and well as those of its customers. We first describe the generic form of the GP problem, and then use a hypothetical example to fill in the relevant variables.

Generic Form for a Goal Programming Problem

$$\textit{Minimize } Z = P_1 d_1^- + P_2 d_2^- + P_3 d_3^+ + P_4 d_4^+$$

$$st:$$

$$\begin{array}{ccccccccccccc}
x_1 & + & x_2 & + & x_3 & + & d_1^- & - & d_1^+ & = & RHS_1 \\
x_1 & + & x_2 & + & x_3 & + & d_2^- & - & d_2^+ & = & RHS_2 \\
 & & x_2 & & & + & d_3^- & - & d_3^+ & = & RHS_3 \\
 & & & & x_3 & + & d_4^- & - & d_4^+ & = & RHS_4
\end{array}$$

$$x_j,\ d_i^-,\ d_i^+ \geq 0$$

In the example shown above, the Goal Programming problem consists of an objective function and a series of goal constraints. The objective function identifies the set of goals to be achieved. The goal constraints specify what each alternative can contribute toward achieving each of the identified goals.

The objective function is set up to minimize the deviation, d_i, from a series of goal priorities, P_i. The subscript i references the index of either the goal priority or the constraint number. P_2, for example, represents the second goal to be achieved. On the other hand, d_2 represents the level of deviation from the second goal constraint. Finally, the plus or minus superscript reflects whether the goal is to minimize the over or underachievement of the goal priority. For example, if we choose to maximize employment, then we are trying to minimize underachievement and the notation is shown as d_i^-. If we are, instead, trying to minimize pollution, then we are trying to minimize the over achievement of emissions. In this case, the notation is shown as d_i^+.

The system of constraints show the alternatives or decision variables, X_i, that specifies the rate at which each alternative will contribute toward the achievement of the desired goal. The goal itself is specified as RHS_i, or right-hand side to be solved for constraint i. If the goal is exactly achieved, then both deviational variables are 0. If the solution falls 100 short of the desired goal, then d_i^- equals 100. At the same time, if the solution exceeds the goal by 100, then d_i^+ equals 100.

Adapting the Algorithm to Climate Change Mitigation Strategies

Although relatively new to the investigation of climate mitigation strategies, the GP concept has been previously used in a series of community-based studies (Lee et al, 1986; and Laitner and Kegel, 1988, 1989). Brody and Rosen discussed a multi-attribute analysis in a collaborative process involving electric facility siting (1994). Building on this prior work, and incorporating information from the growing successes within the Energy Star Program (CPD, 1999), the goal programming technique can be readily adapted to investigating climate change mitigation strategies. The debate about climate change has raised a number of goals and concerns from various stakeholder perspectives that can be translated into the objectives and constraints of a GP model. First is the goal to significantly reduce national emissions of greenhouse gases including emissions of carbon dioxide, the primary greenhouse gas. At the same time, much of the nation is facing new requirements for reducing emissions of local air pollution such as emissions of nitrogen oxides.

One large concern is that effectively addressing climate change over the next couple of decades will have a large negative impact on the nation's competitiveness and overall economic activity. Very often this last concern is manifested in terms of possible losses in employment. Another concern is that there are insufficient investment dollars available to invest in enough new technology so as to have a sizable impact on national emissions over the next decade.

There is also a growing body of information on a number of climate change mitigation strategies. There is available information on the investment costs, environmental impact, net jobs impact, and energy costs for various technologies as well as national policies. These mitigation strategies become the decision variables in the model (Interlaboratory Working Group, 2000; Bernow et al, 1999; Geller, et al, 1999; and Laitner et al, 1999).

Goal programming will allow analysts to investigate the role that different climate change mitigation strategies can play in an overall national effort to reduce greenhouse gas emissions, while satisfying a desired list of other outcomes. The set of desired outcomes may be a sizable growth in jobs, sizable environmental co-benefits, positive economic growth, and a reasonable level of technology investment.

To illustrate this approach we have chosen a range of climate mitigation strategies in the commercial electricity sector, including strategies on both the energy supply side and the energy demand side. On the supply side, we have chosen to include the conventional mix of generation plants, combined heat and power systems, and solar-generated power. On the demand side, we have included three technology bundles in the commercial buildings sector, an area that represents sizable opportunity for cost-effective investment over the next decade. The technology bundles include traditional building efficiency improvements, energy efficient (Energy Star) office equipment, and Energy Star building improvement projects. Energy Star building improvements incorporate the systems interactions within a building and therefore require more up-front investment while offering greater environmental benefits and cost savings.

Results from an Energy Star Building Analysis

To further illustrate the capabilities of the goal programming technique, we will focus on achieving the most desirable mix of supply and demand side technologies that can meet the anticipated electricity requirements in the commercial buildings sector. In the year 2010, for example, the Annual Energy Outlook 2000 indicates that the total electricity demand will be 1,277 billion kilowatt-hours (EIA 1999). That level of demand anticipates a mix of building technologies, equipment and appliances. Moreover, that demand will be met through a specified mix of electric generators.

Normally, the models evaluate a mix of demand and supply technologies using assumed cost characteristics and sector-differentiated discount rates to determine a least-cost strategy. But with the goal programming technique we can examine how the pattern of technologies might change given a total of four goals to be satisfied rather than one. If, in addition to minimizing costs, we were also interested in maximizing employment as well as minimizing both carbon and NOx emissions, then we can set up a GP problem to help sort through the alternatives given these multiple, perhaps conflicting, objectives.

The set of chosen strategies represents a range of environmental impacts, investment requirements, net job impacts, and cost savings. The key factors for these technologies as well as their maximum expected penetration by 2010 are presented in Table 2.

The first data column in Table 2 shows the estimated cost per kilowatt-hour (kWh) associated with each of the six alternatives.[3] At the end of that first column, the table also shows the AEO2000 projection of the total electric bill for the commercial building sector in 2010 ($81.2 billion in 1998 dollars).

3. For purposes of this illustration, these annual cost values are adapted from information within the available literature. They are intended only as representative rather than precise values.

Table 2. A Goal Programming Problem for 2010 Commercial Electricity Supply

Decision Variable	*Minimize Cost*	*Minimize NOx*	*Minimize Carbon*	*Maximize Jobs*	*Maximum Resource*
Conventional Electric Supply	$0.064/kWh	1.45 tons/GWh	174.2 tonnes/GWh	0.38 jobs/GWh	n/a
Combined Heat & Power Systems	$0.045	0.12	100	0.45	100,000 GWh
Solar-Generated Electricity	$0.220	0	0	0.25	10,000
Conventional Efficiency Upgrade	$0.057	0	0	0.40	100,000
Energy Star Building Upgrade	$0.047	0	0	0.47	400,000
Energy Star Office Products	$0.032	0	0	0.56	50,000
Current 2010 Projections	$81.2 billion	1.85 million tons	222.45 million tonnes	485,000 jobs	
System or Desired Goals	$77 billion	1.68 million tons	180 million tonnes	534,000 jobs	

Notes: The annual cost estimates shown above are intended only to illustrate the magnitude of cost differences among the competing technologies that are reviewed here. While they reflect real world cost comparisons, the values should not be interpreted as precise cost estimates for any specific technology. Although the CHP and other technologies show little or no emission rates compared to conventional electric supply resources, the actual benefit will be based upon the displacement of a marginal rather than average unit. In this case, it is assumed the displaced unit will be a gas turbine. Finally, the employment coefficients were derived using standard input-output modeling techniques. Again, they are intended only to illustrate the magnitude of impact among the several technology bundles referenced in this exercise. Readers interested in any of this information should contact Skip Laitner by phone at (202) 564-9833, or by email at laitner.skip@epa.gov.

The second and third data columns provide the impact associated with nitrogen oxide (NOx) and carbon emissions for each of the technologies. The unit of measurement is short tons of NOx and metric tons of carbon per million kWh, or per gigawatt-hour (GWh). According to AEO2000, commercial electric services in the year 2010 can be expected to emit about 1.85 million short tons of NOx and 222.45 million metric tons of carbon equivalent. The fourth data column maps out the estimated employment impacts in terms of the number of jobs per GWh. The direct and indirect employment associated with electricity generation in 2010 is expected to be about 485,000 jobs (Laitner, 2000). Finally, the last data column shows the maximum level of production available for each resource or technology given both the technology characteristics and market conditions expected for 2010.

The AEO2000 forecast for 2010 already assumes a certain level of energy efficiency and supply side improvements embodied within the electricity projection of 1,277 terawatt-hours (TWh). The question to be answered here is whether the additional goals might cause a change in the pattern of resources deployed by the year 2010. The first step in setting up a GP problem to examine this issue is to identify initial goal levels for each of the four priorities. Hence, we might ask whether a different mix of technologies can lower overall electricity expenditures by 5 percent of the reference case projections. This would reduce the total from $81.2 to $77 billion. As the same time, we might ask whether carbon emissions might be reduced by 20 percent (to 180 million tonnes) and NOx emissions by 10 percent (to 1.68 million tons). Finally, the question might be asked whether employment can be increased by 10 percent over the reference case estimates (from 485,000 to 534,000 jobs). Each of these goal levels is shown in the bottom row of Table 2 referenced as "system or desired goals."

With the goals and the data reasonably in place, we can now set up a GP problem to see what level of individual goals might be satisfied. Perhaps just as important, we can explore an alternative mix of technologies to see whether they make sense, and whether the goals can be achieved.[4]

Table 3. Analysis of Resource Utilization for 2010

Technology Variable	***Starting Value***	***Solution Value***
Conventional Electric Supply	1,277 TWh	774 TWh
Combined Heat and Power	0	53
Solar Electric Technologies	0	0
Standard Office Upgrade	0	0
Energy Star Office Upgrade	0	400
Energy Star Office Products	0	50
Total Resources Deployed	1,277	1,277

4. The analysis was carried out using the GPGO model developed by S.M. Lee (1994), a preemptive goal program algorithm now widely used. We are exploring the use of other models, including the GPSYS system (Jones et al, 1998).

Table 3 shows the recommended level of output from each of the six technologies used in this illustrative example.

As it turns out, the specified goals appear to be met using the mix of available resources shown in the last column of Table 3. Given this distribution of resources, Table 4 shows the resulting impacts based on the contribution that each of the technologies is expected to make toward the four goals previously discussed.

Table 4. Analysis of Deviations from the Goal Constraints

System or Goal Constraint	*Starting Value*	*d* $^{+}$	*d* $^{-}$
Total Demand	1277 TWh	0	0
Standard Upgrade	100 TWh	0	100
Energy Star Upgrade	400 TWh	0	0
Combined Heat and Power	100 TWh	0	47
Solar Electric	10 TWh	0	10
Office Products	50 TWh	0	0
Carbon Emissions	180 MtC	0	40
NOx Emissions	1.68 Million tons	0	0.55
Employment	534,000 jobs	0	0
Electricity Bill	$77 billion	0	5

Again, all of the goals appear to have been met, although several have been exceeded. For example, given the technology characteristics described above, the employment goal has been exactly satisfied. In other words, based upon the deployment of resources described in Table 3, the net direct and indirect employment can be expected to increase from 485,000 to 534,000 jobs in the year 2010. The desired goal of 534,000 jobs is neither over achieved (where d^{+} is greater than 0), nor underachieved (where d^{-} is less than 0).

At the same time, the carbon emissions have been reduced by 40 MtC (to 140 MtC) compared to the target of 180 MtC, while NOx emissions have been reduced by 550,000 tons beyond the desired limit (1.13 compared to 1.68 million tons). Finally the electricity bill is shown to be about $5 billion less than the suggested target of $77 billion, and about $9 billion less than the $81.2 billion projected in the reference case.

To reach these levels of attainment, neither the solar electric nor the conventional efficiency upgrades were selected. At the same time, the CHP resource was utilized to only 53 of the available 100 TWh while the Energy Star upgrades were fully utilized. The slack in available resources indicates further opportunity to decrease both NOx and carbon emissions. However, tightness in achieving the employment goal, and the expected higher costs associated with the solar resources suggests that the electricity bill might rise from this alternative scenario while employment might be pushed downward a bit. Still, additional runs would likely show that a further reduction in pollutants might continue to show a net positive return to the reference case itself.

Conclusion

This paper explains a limited exercise designed only to highlight the use of goal programming or other multiattribute decision tools. The results of this scenario analysis should not be taken as a forecast of specific impacts if the technologies are deployed as indicated. Among other things, a more complete result would incorporate both demand and supply interactions as well as price and income effects — and their respective influences on the cost and performance characteristics of the technologies described. Finally, a much greater array of technologies would undoubtedly be part of the resource mix. Despite the limitations of this heuristic exercise, however, the results are sufficiently compelling to suggest that more research be undertaken to actively bring the GP algorithm and other multivariate evaluation assessments to the forefront of policy analysis. This would likely open up a broader range of understanding about the full costs and benefits of the many decisions associated with climate change mitigation.

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