

Pearson New International Edition

**Managerial Decision Modeling
with Spreadsheets**
Balakrishnan Render Stair
Third Edition



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Introduction to Managerial Decision Modeling

LEARNING OBJECTIVES

After completing this chapter, students will be able to:

1. Define *decision model* and describe the importance of such models.
2. Understand the two types of decision models: deterministic and probabilistic models.
3. Understand the steps involved in developing decision models in practical situations.
4. Understand the use of spreadsheets in developing decision models.
5. Discuss possible problems in developing decision models.

CHAPTER OUTLINE

- 1 What Is Decision Modeling?
- 2 Types of Decision Models
- 3 Steps Involved in Decision Modeling
- 4 Spreadsheet Example of a Decision Model: Tax Computation
- 5 Spreadsheet Example of a Decision Model: Break-Even Analysis
- 6 Possible Problems in Developing Decision Models
- 7 Implementation—Not Just the Final Step

Summary • Glossary • Discussion Questions and Problems

The companion website for this text is www.pearsonhighered.com/balakrishnan.

1 What Is Decision Modeling?

Decision modeling is a scientific approach to decision making.

Although there are several definitions of **decision modeling**, we define it here as a scientific approach to managerial decision making. Alternatively, we can define it as the development of a **model** (usually mathematical) of a real-world problem scenario or environment. The resulting model should typically be such that the decision-making process is not affected by personal bias, whim, emotions, and guesswork. This model can then be used to provide insights into the solution of the managerial problem. Decision modeling is also commonly referred to as *quantitative analysis*, *management science*, or *operations research*. In this text, we prefer the term *decision modeling* because we will discuss all modeling techniques in a managerial decision-making context.

Organizations such as American Airlines, United Airlines, IBM, Google, UPS, FedEx, and AT&T frequently use decision modeling to help solve complex problems. Although mathematical tools have been in existence for thousands of years, the formal study and application of quantitative (or mathematical) decision modeling techniques to practical decision making is largely a product of the twentieth century. The decision modeling techniques studied here have been applied successfully to an increasingly wide variety of complex problems in business, government, health care, education, and many other areas. Many such successful uses are discussed throughout this text.

It isn't enough, though, just to know the mathematical details of how a particular decision modeling technique can be set up and solved. It is equally important to be familiar with the limitations, assumptions, and specific applicability of the model. The correct use of decision modeling techniques usually results in solutions that are timely, accurate, flexible, economical, reliable, easy to understand, and easy to use.

2 Types of Decision Models

Decision models can be broadly classified into two categories, based on the type and nature of the decision-making problem environment under consideration: (1) deterministic models and (2) probabilistic models. We define each of these types of models in the following sections.

Deterministic Models

Deterministic models assume that all the relevant input data values are known with certainty; that is, they assume that all the information needed for modeling a decision-making problem environment is available, with fixed and known values. An example of such a model is the case of Dell Corporation, which makes several different types of PC products (e.g., desktops, laptops), all of which compete for the same resources (e.g., labor, hard disks, chips, working capital). Dell knows the specific amounts of each resource required to make one unit of each type of PC, based on the PC's design specifications. Further, based on the expected selling price and cost prices of various resources, Dell knows the expected profit contribution per unit of

Deterministic means with complete certainty.

HISTORY The Origins of Decision Modeling

Decision modeling has been in existence since the beginning of recorded history, but it was Frederick W. Taylor who, in the early 1900s, pioneered the principles of the scientific approach to management. During World War II, many new scientific and quantitative techniques were developed to assist the military. These new developments were so successful that after World War II, many companies started using similar techniques in managerial decision making and planning. Today, many organizations employ a staff of operations research or

management science personnel or consultants to apply the principles of scientific management to problems and opportunities. The terms *management science*, *operations research*, and *quantitative analysis* can be used interchangeably, though here we use *decision modeling*.

The origins of many of the techniques discussed in this text can be traced to individuals and organizations that have applied the principles of scientific management first developed by Taylor; they are discussed in *History* boxes scattered throughout the text.

each type of PC. In such an environment, if Dell decides on a specific production plan, it is a simple task to compute the quantity required of each resource to satisfy that production plan. For example, if Dell plans to ship 50,000 units of a specific laptop model, and each unit includes a pair of 2.0GB SDRAM memory chips, then Dell will need 100,000 units of these memory chips. Likewise, it is easy to compute the total profit that will be realized by this production plan (assuming that Dell can sell all the laptops it makes).

The most commonly used deterministic modeling technique is linear programming.

Perhaps the most common and popular deterministic modeling technique is linear programming (LP).

Probabilistic Models

Some input data are unknown in probabilistic models.

In contrast to deterministic models, **probabilistic models** (also called *stochastic models*) assume that some *input data* values are not known with certainty. That is, they assume that the values of some important variables will not be known *before* decisions are made. It is therefore important to incorporate this “ignorance” into the model. An example of this type of model is the decision of whether to start a new business venture. As we have seen with the high variability in the stock market during the past several years, the success of such ventures is unsure. However, investors (e.g., venture capitalists, founders) have to make decisions regarding this type of venture, based on their expectations of future performance. Clearly, such expectations are not guaranteed to occur. In recent years, we have seen several examples of firms that have yielded (or are likely to yield) great rewards to their investors (e.g., Google, Facebook, Twitter) and others that have either failed (e.g., eToys.com, Pets.com) or been much more modest in their returns.

Another example of probabilistic modeling to which students may be able to relate easily is their choice of a major when they enter college. Clearly, there is a great deal of uncertainty regarding several issues in this decision-making problem: the student’s aptitude for a specific major, his or her actual performance in that major, the employment situation in that major in four years, etc. Nevertheless, a student must choose a major early in his or her college career. Recollect your own situation. In all likelihood, you used your own assumptions (or expectations) regarding the future to evaluate the various alternatives (i.e., you developed a “model” of the decision-making problem). These assumptions may have been the result of information from various sources, such as parents, friends, and guidance counselors. The important point to note here is that none of this information is guaranteed, and no one can predict with 100% accuracy what exactly will happen in the future. Therefore, decisions made with this information, while well thought out and well intentioned, may still turn out to not be the best choices. For example, how many of your friends have changed majors during their college careers?

Because their results are not guaranteed, does this mean that probabilistic decision models are of limited value? The answer is an emphatic no. Probabilistic modeling techniques provide a structured approach for managers to incorporate uncertainty into their models and to evaluate decisions under alternate expectations regarding this uncertainty. They do so by using probabilities on the “random,” or unknown, variables. Probabilistic modeling techniques include decision analysis, queuing, simulation, and forecasting. Two other techniques, project management and inventory control, include aspects of both deterministic and probabilistic modeling. For each modeling technique, we discuss what kinds of criteria can be used when there is uncertainty and how to use these models to identify the preferred decisions.

Probabilistic models use probabilities to incorporate uncertainty.

Because uncertainty plays a vital role in probabilistic models, some knowledge of basic probability and statistical concepts is useful.

The decision modeling process starts with data.

Both qualitative and quantitative factors must be considered.

Spreadsheet packages are capable of handling many decision modeling techniques.

Several add-ins for Excel are included on the Companion Website for this text, www.pearsonhighered.com/balakrishnan.

Quantitative versus Qualitative Data

Any decision modeling process starts with data. Like raw material for a factory, these data are manipulated or processed into information that is valuable to people making decisions. This processing and manipulating of raw data into meaningful information is the heart of decision modeling.

In dealing with a decision-making problem, managers may have to consider both qualitative and quantitative factors. For example, suppose we are considering several different investment alternatives, such as certificates of deposit, the stock market, and real estate. We can use *quantitative* factors such as rates of return, financial ratios, and cash flows in our decision model to guide our ultimate decision. In addition to these factors, however, we may also wish to consider *qualitative* factors such as pending state and federal legislation, new technological breakthroughs, and the outcome of an upcoming election. It can be difficult to quantify these qualitative factors.

Due to the presence (and relative importance) of qualitative factors, the role of quantitative decision modeling in the decision-making process can vary. When there is a lack of qualitative factors, and when the problem, model, and input data remain reasonably stable and steady over time, the results of a decision model can automate the decision-making process. For example, some companies use quantitative inventory models to determine automatically when to order additional new materials and how much to order. In most cases, however, decision modeling is an aid to the decision-making process. The results of decision modeling should be combined with other (qualitative) information while making decisions in practice.

Using Spreadsheets in Decision Modeling

In keeping with the ever-increasing presence of technology in modern times, computers have become an integral part of the decision modeling process in today's business environments. Until the early 1990s, many of the modeling techniques discussed here required specialized software packages in order to be solved using a computer. However, spreadsheet packages such as Microsoft Excel have become increasingly capable of setting up and solving most of the decision modeling techniques commonly used in practical situations. For this reason, the current trend in many college courses on decision modeling focuses on spreadsheet-based instruction. In keeping with this trend, we discuss the role and use of spreadsheets (specifically Microsoft Excel) during our study of the different decision modeling techniques presented here.

In addition to discussing the use of some of Excel's built-in functions and procedures (e.g., [Goal Seek](#), [Data Table](#), [Chart Wizard](#)), we also discuss several add-ins for Excel. The [Data Analysis](#) and [Solver](#) add-ins come standard with Excel; others are included on the Companion Website.



IN ACTION

IBM Uses Decision Modeling to Improve the Productivity of Its Sales Force

IBM is a well-known multinational computer technology, software, and services company with over 380,000 employees and revenue of over \$100 billion. A majority of IBM's revenue comes from services, including outsourcing, consulting, and systems integration. At the end of 2007, IBM had approximately 40,000 employees in sales-related roles.

Recognizing that improving the efficiency and productivity of this large sales force can be an effective operational strategy to drive revenue growth and manage expenses, IBM Research

developed two broad decision modeling initiatives to facilitate this issue. The first initiative provides a set of analytical models designed to identify new sales opportunities at existing IBM accounts and at noncustomer companies. The second initiative allocates sales resources optimally based on field-validated analytical estimates of future revenue opportunities in market segments. IBM estimates the revenue impact of these two initiatives to be in the several hundreds of millions of dollars each year.

Source: Based on R. Lawrence et al. "Operations Research Improves Sales Force Productivity at IBM," *Interfaces* 40, 1 (January-February 2010): 33–46.

3 Steps Involved in Decision Modeling

The decision modeling process involves three steps.

It is common to iterate between the three steps.

Formulation is the most challenging step in decision modeling.

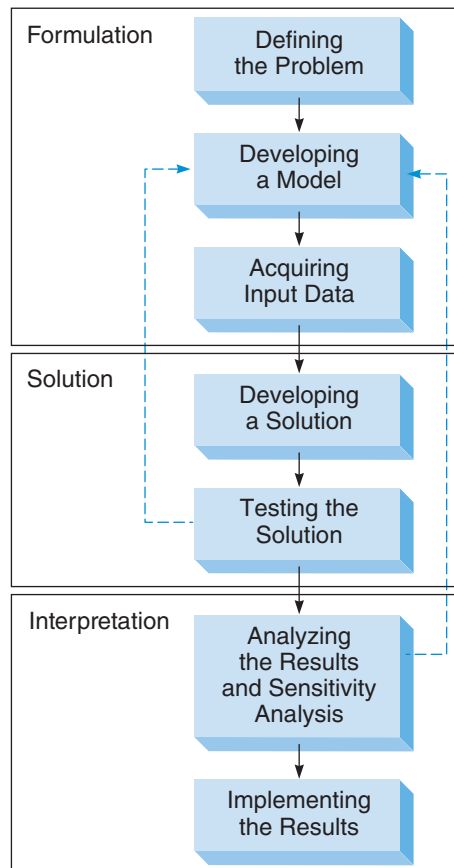
Regardless of the size and complexity of the decision-making problem at hand, the decision modeling process involves three distinct steps: (1) formulation, (2) solution, and (3) interpretation. Figure 1 provides a schematic overview of these steps, along with the components, or parts, of each step. We discuss each of these steps in the following sections.

It is important to note that it is common to have an iterative process between these three steps before the final solution is obtained. For example, testing the solution (see Figure 1) might reveal that the model is incomplete or that some of the input data are being measured incorrectly. This means that the formulation needs to be revised. This, in turn, causes all the subsequent steps to be changed.

Step 1: Formulation

Formulation is the process by which each aspect of a problem scenario is translated and expressed in terms of a mathematical model. This is perhaps the most important and challenging step in decision modeling because the results of a poorly formulated problem will almost surely be incorrect. It is also in this step that the decision maker’s ability to analyze a problem rationally comes into play. Even the most sophisticated software program will not automatically formulate a problem. The aim in formulation is to ensure that the mathematical model completely

FIGURE 1
The Decision Modeling Approach



addresses all the issues relevant to the problem at hand. Formulation can be further classified into three parts: (1) defining the problem, (2) developing a model, and (3) acquiring input data.

DEFINING THE PROBLEM The first part in formulation (and in decision modeling) is to develop a clear, concise statement of the problem. This statement gives direction and meaning to all the parts that follow it.

Defining the problem can be the most important part of formulation.

In many cases, defining the problem is perhaps the most important, and the most difficult, part. It is essential to go beyond just the symptoms of the problem at hand and identify the true causes behind it. One problem may be related to other problems, and solving a problem without regard to its related problems may actually make the situation worse. Thus, it is important to analyze how the solution to one problem affects other problems or the decision-making environment in general. Experience has shown that poor problem definition is a major reason for failure of management science groups to serve their organizations well.

When a problem is difficult to quantify, it may be necessary to develop *specific, measurable* objectives. For example, say a problem is defined as inadequate health care delivery in a hospital. The objectives might be to increase the number of beds, reduce the average number of days a patient spends in the hospital, increase the physician-to-patient ratio, and so on. When objectives are used, however, the real problem should be kept in mind. It is important to avoid obtaining specific and measurable objectives that may not solve the real problem.

DEVELOPING A MODEL Once we select the problem to be analyzed, the next part is to develop a decision model. Even though you might not be aware of it, you have been using models most of your life. For example, you may have developed the following model about friendship: Friendship is based on reciprocity, an exchange of favors. Hence, if you need a favor, such as a small loan, your model would suggest that you ask a friend.

The types of models include physical, scale, schematic, and mathematical models.

Of course, there are many other types of models. An architect may make a physical model of a building he or she plans to construct. Engineers develop scale models of chemical plants, called pilot plants. A schematic model is a picture or drawing of reality. Automobiles, lawn mowers, circuit boards, typewriters, and numerous other devices have schematic models (drawings and pictures) that reveal how these devices work.

What sets decision modeling apart from other modeling techniques is that the models we develop here are mathematical. A *mathematical model* is a set of mathematical relationships. In most cases, these relationships are expressed as equations and inequalities, as they are in a spreadsheet model that computes sums, averages, or standard deviations.

A variable is a measurable quantity that is subject to change.

Although there is considerable flexibility in the development of models, most of the models presented here contain one or more variables and parameters. A **variable**, as the name implies, is a measurable quantity that may vary or that is subject to change. Variables can be controllable or uncontrollable. A controllable variable is also called a *decision variable*. An example is how many inventory items to order. A **problem parameter** is a measurable quantity that is inherent in the problem, such as the cost of placing an order for more inventory items. In most cases, variables are unknown quantities, whereas parameters (or input data) are known quantities.

A parameter is a measurable quantity that usually has a known value.

All models should be developed carefully. They should be solvable, realistic, and easy to understand and modify, and the required input data should be obtainable. A model developer has to be careful to include the appropriate amount of detail for the model to be solvable yet realistic.

ACQUIRING INPUT DATA Once we have developed a model, we must obtain the **input data** to be used in the model. Obtaining accurate data is essential because even if the model is a perfect representation of reality, improper data will result in misleading results. This situation is called *garbage in, garbage out* (GIGO). For larger problems, collecting accurate data can be one of the most difficult aspects of decision modeling.

Garbage in, garbage out means that improper data will result in misleading results.

Several sources can be used in collecting data. In some cases, company reports and documents can be used to obtain the necessary data. Another source is interviews with employees or other persons related to the firm. These individuals can sometimes provide excellent information, and their experience and judgment can be invaluable. A production supervisor, for example, might be able to tell you with a great degree of accuracy the amount of time that it takes to manufacture a particular product. Sampling and direct measurement provide other sources of data for the model. You may need to know how many pounds of a raw material are

used in producing a new photochemical product. This information can be obtained by going to the plant and actually measuring the amount of raw material that is being used. In other cases, statistical sampling procedures can be used to obtain data.

Step 2: Solution

The solution step is when the mathematical expressions resulting from the formulation process are actually solved to identify the optimal solution. Until the mid-1990s, typical courses in decision modeling focused a significant portion of their attention on this step because it was the most difficult aspect of studying the modeling process. As stated earlier, thanks to computer technology, the focus today has shifted away from the detailed steps of the solution process and toward the availability and use of software packages. The solution step can be further classified into two parts: (1) developing a solution and (2) testing the solution.

DEVELOPING A SOLUTION Developing a solution involves manipulating the model to arrive at the best (or optimal) solution to the problem. In some cases, this may require that a set of mathematical expressions be solved to determine the best decision. In other cases, you can use a trial-and-error method, trying various approaches and picking the one that results in the best decision. For some problems, you may wish to try all possible values for the variables in the model to arrive at the best decision; this is called *complete enumeration*. For problems that are quite complex and difficult, you may be able to use an algorithm. An *algorithm* consists of a series of steps or procedures that we repeat until we find the best solution. Regardless of the approach used, the accuracy of the solution depends on the accuracy of the input data and the decision model itself.

TESTING THE SOLUTION Before a solution can be analyzed and implemented, it must be tested completely. Because the solution depends on the input data and the model, both require testing. There are several ways to test input data. One is to collect additional data from a different source and use statistical tests to compare these new data with the original data. If there are significant differences, more effort is required to obtain accurate input data. If the data are accurate but the results are inconsistent with the problem, the model itself may not be appropriate. In this case, the model should be checked to make sure that it is logical and represents the real situation.

Step 3: Interpretation and Sensitivity Analysis

Assuming that the formulation is correct and has been successfully implemented and solved, how does a manager use the results? Here again, the decision maker's expertise is called upon because it is up to him or her to recognize the implications of the results that are presented. We discuss this step in two parts: (1) analyzing the results and sensitivity analysis and (2) implementing the results.

ANALYZING THE RESULTS AND SENSITIVITY ANALYSIS Analyzing the results starts with determining the implications of the solution. In most cases, a solution to a problem will result in some kind of action or change in the way an organization is operating. The implications of these actions or changes must be determined and analyzed before the results are implemented.

Because a model is only an approximation of reality, the sensitivity of the solution to changes in the model and input data is an important part of analyzing the results. This type of analysis is called sensitivity, postoptimality, or what-if analysis. **Sensitivity analysis** is used to determine how much the solution will change if there are changes in the model or the input data. When the optimal solution is very sensitive to changes in the input data and the model specifications, additional testing must be performed to make sure the model and input data are accurate and valid.

The importance of sensitivity analysis cannot be overemphasized. Because input data may not always be accurate or model assumptions may not be completely appropriate, sensitivity analysis can become an important part of decision modeling.

IMPLEMENTING THE RESULTS The final part of interpretation is to *implement* the results. This can be much more difficult than one might imagine. Even if the optimal solution will result in millions of dollars in additional profits, if managers resist the new solution, the model is of no value. Experience has shown that a large number of decision modeling teams have failed in their efforts because they have failed to implement a good, workable solution properly.

In the solution step, we solve the mathematical expressions in the formulation.

An algorithm is a series of steps that are repeated.

The input data and model determine the accuracy of the solution.

Analysts test the data and model before analyzing the results.

Sensitivity analysis determines how the solutions will change with a different model or input data.

The solution should be closely monitored even after implementation.

After the solution has been implemented, it should be closely monitored. Over time, there may be numerous changes that call for modifications of the original solution. A changing economy, fluctuating demand, and model enhancements requested by managers and decision makers are a few examples of changes that might require an analysis to be modified.

4 Spreadsheet Example of a Decision Model: Tax Computation

A decision modeling example.

Now that we have discussed what a decision model is, let us develop a simple model for a real-world situation that we all face each year: paying taxes. Sue and Robert Miller, a newly married couple, will be filing a joint tax return for the first time this year. Because both work as independent contractors (Sue is an interior decorator, and Rob is a painter), their projected income is subject to some variability. However, because their earnings are not taxed at the source, they know that they have to pay estimated income taxes on a quarterly basis, based on their estimated taxable income for the year. To help calculate this tax, the Millers would like to set up a spreadsheet-based decision model. Assume that they have the following information available:

- Their only source of income is from their jobs.
- They would like to put away 5% of their total income in a retirement account, up to a maximum of \$6,000. Any amount they put in that account can be deducted from their total income for tax purposes.
- They are entitled to a personal exemption of \$3,700 each. This means that they can deduct \$7,400 ($= 2 \times \$3,700$) from their total income for tax purposes.
- The standard deduction for married couples filing taxes jointly this year is \$11,600. This means that \$11,600 of their income is free from any taxes and can be deducted from their total income.
- They do not anticipate having any other deductions from their income for tax purposes.
- The tax brackets for this year are 10% for the first \$17,000 of taxable income, 15% between \$17,001 and \$69,000 and 25% between \$69,001 and \$139,350. The Millers don't believe that tax brackets beyond \$139,350 are relevant for them this year.

Excel Notes

- The Companion Website for this text, at www.pearsonhighered.com/balakrishnan, contains the Excel file for each sample problem discussed here. The relevant file name is shown in the margin next to each example.
- In each of our Excel layouts, for clarity, we color code the cells as follows:
 - Variable input cells, in which we enter specific values for the variables in the problem, are shaded yellow.
 - Output cells, which show the results of our analysis, are shaded green.
- We have used callouts to annotate the screenshots in this text to highlight important issues in the decision model.
- Wherever necessary, many of these callouts are also included as comments in the Excel files themselves, making it easier for you to understand the logic behind each model.



File: 1-1.xls, sheet: 1-1A

Wherever possible, titles, labels, and comments should be included in the model to make them easier to understand.

Rather than use constants directly in formulas, it is preferable to make them cell references.

Screenshot 1A shows the formulas that we can use to develop a decision model for the Millers. Just as we have done for this Excel model (and all other models in this text), we strongly recommend that you get in the habit of using descriptive titles, labels, and comments in any decision model that you create. The reason for this is very simple: In many real-world settings, decision models that you create are likely to be passed on to others. In such cases, the use of comments will help them understand your thought process. Perhaps an appropriate question you should always ask yourself is “Will I understand this model a year or two after I first write it?” If appropriate labels and comments are included in the model, the answer should always be yes.

In Screenshot 1A, the known problem parameter values (i.e., constants) are shown in the box labeled Known Parameters. Rather than use these known constant values directly in the formulas, we recommend that you develop the habit of entering each known value in a cell and then using that cell reference in the formulas. In addition to being more “elegant,” this way of modeling has the advantage of making any future changes to these values easy.

SCREENSHOT 1A
Formula View of Excel
Layout for the Millers’
Tax Computation

	A	B	C	D	E
1	Millers' Tax Computation				
2					
3	Known Parameters				
4	Retirement Savings %	0.05			
5	Maximum savings	6000			
6	Personal exemption	3700	per person		
7	Standard deduction	11600			
8	Tax rates	0.1	1	to	17000
9		0.15	17001	to	69000
10		0.25	69001	to	139350
11					
12	Variables				
13	Sue's estimated income				
14	Rob's estimated income				
15					
16	Tax Computation				
17	Total income	=B13+B14			
18	Retirement savings	=MIN(B4*B17,B5)			
19	Personal exemptions	=2*B6			
20	Standard deduction	=B7			
21	Taxable income	=MAX(0,B17-SUM(B18:B20))			
22	Tax @ 10% rate	=B8*MIN(B21,E8)			
23	Tax @ 15% rate	=IF(B21>E8,B9*(MIN(B21,E9)-E8),0)			
24	Tax @ 25% rate	=IF(B21>E9,B10*(MIN(B21,E10)-E9),0)			
25	Total tax	=SUM(B22:B24)			
26	Estimated tax per quarter	=B25/4			

This box shows all the *known* input parameter values.

This box shows the two input variables.

Minimum of (5% of total income, \$6,000)

Maximum of (0, taxable income)

10% tax up to \$17,000

15% tax between \$17,001 and \$69,000. This tax is calculated only if taxable income exceeds \$17,000.

25% tax between \$69,001 and \$139,350. This tax is calculated only if taxable income exceeds \$69,000.

Cells B13 and B14 denote the only two variable data entries in this decision model: Sue’s and Rob’s estimated incomes for this year. When we enter values for these two variables, the results are computed in cells B17:B26 and presented in the box labeled Tax Computation.

Cell B17 shows the total income. The **MIN** function is used in cell B18 to specify the tax-deductible retirement contribution as the smaller value of 5% of total income and \$6,000. Cells B19 and B20 set the personal exemptions and the standard deduction, respectively. The net taxable income is shown in cell B21, and the **MAX** function is used here to ensure that this amount is never below zero. The taxes payable at the 10%, 15%, and 25% rates are then calculated in cells B22, B23, and B24, respectively. In each of these cells, the **MIN** function is used to ensure that only the incremental taxable income is taxed at a given rate. (For example, in cell B23, only the portion of taxable income above \$17,000 is taxed at the 15% rate, up to an upper limit of \$69,000.) The **IF** function is used in cells B23 and B24 to check whether the taxable income exceeds the lower limit for the 15% and 25% tax rates, respectively. If the taxable income does not exceed the relevant lower limit, the **IF** function sets the tax payable at that rate to zero. Finally, the total tax payable is computed in cell B25, and the estimated quarterly tax is computed in cell B26.

Now that we have developed this decision model, how can the Millers actually use it? Suppose Sue estimates her income this year at \$55,000 and Rob estimates his at \$50,000. We enter these values in cells B13 and B14, respectively. The decision model immediately lets us know that the Millers have a taxable income of \$80,750 and that they should pay estimated taxes of \$3,109.38 each quarter. These input values, and the resulting computations, are shown in Screenshot 1B. We can use this decision model in a similar fashion with any other estimated income values for Sue and Rob.

Observe that the decision model we have developed for the Millers’ example does not optimize the decision in any way. That is, the model simply computes the estimated taxes for a given income level. It does not, for example, determine whether these taxes can be reduced in some way through better tax planning.

Excel’s MAX, MIN, and IF functions have been used in this decision model.



File: 1-1.xls, sheet: 1-1B