Research Note: Review of Problem-solving in Management Sciences

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We review some of Operations Research / Management Sciences basic textbook in search of problem solving steps in managerial problem. Next we examine the detail of issues involved in the initial stage: problem identification.

Subject classification: Problem solving, Management Sciences, Problem Identification

1. Introduction

Most of introductory Operations Research/Management Sciences (OR/MS) textbooks cover two contents at the beginning of the book. The first chapter usually deals with "how to solve OR/MS problem". The next chapter discusses Linear Programming (LP). The level of sophistication of these two topics are far apart. LP chapter describes what is about in theory, and what to do in practice in sufficiently in details. But the the first "how to" chapter brings us almost nowhere. We try to investigate this Managerial Problem Solving Steps (MPSS).

Development of MPSS originates from the classic tool: Analysis, and algorithm. The major output of it is decomposition. The decomposition roots from the basic strategy of "divide, and conquer". We OR/MS people has been fascinated by the charm of mathematics, thus has been reluctant to examine qualitative steps: Problem identification (PI), and Implementation.

At the next section, we will review some of contents from the books we have. Some of the quotation is quite lengthy propagating about ten pages or so. Providing vivid full background data surrounding PI forces us to no other choice.

In the third section, we will cover the properties of managerial decision making. In the fourth section, we will discuss the most important, and crucial stage: Problem Identification. We will not cover implementation phase: another important, and time consuming phase in this paper.

2. Literatures

We will review each of the basic text in reverse chronological order: from most recent to the oldest. Although we quote extensive amount of each book, we do it to obtain the well-grasped perspective in MPSS. Also detailed citation enable us to understand PI stage well because we will know what follows it.

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2.1 Taha

Taha (2007) writes preliminary edition of the book in 1968; thus it inherits some flavor of classic PS steps. The first chapter defines OR. He starts explain it with an exaple, and force students to deeper understanding of it through some problem set. Then he goes on illustrating how to develop a model from a real world. He labels MPSS as "Phases of an OR study" in the sixth section of the first chapter.

Then he lists the following five major steps in page 8:

1. Definition of the problem.
2. Construction of the model.
3. Solution of the model.
4. Validation of the model.
5. Implementation of the solution.

Then he goes on describing each stage. We examine each of his steps.

> **Problem denition** involves defining the scope of the problem under investigation. This function should be carried out by the entire OR team. The aim is to identify three principal elements of the decision problem: (1) description of the decision alternatives, (2) determination of the objective of the study, and (3) specification of the limitations under which the modeled system operates.

He clearly states the goal of this step.

> **Model construction** entails an attempt to translate the problem definition into mathematical relationships. If the resulting model fits one of the standard mathematical models, such as linear programming, we can usually reach a solution by using available algorithms. Alternatively, if the mathematical relationships are too complex to allow the determination of an analytic solution, the OR team may opt to simplify the model and use a heuristic approach, or they may consider the use of simulation, if appropriate. In some cases, mathematical, simulation, and heuristic models may be combined to solve the decision problem, as the case analyses in Chapter 24 demonstrate.

Does our target of MPSS is a mathematical model? Some of our toughest problem may only be described qualitatively.

> **Model solution** is by far the simplest of all OR phases because it entails the use of well-defined optimization algorithms. An important aspect of the model solution phase is sensitivity analysis. It deals with obtaining additional information about the behavior of the optimum solution when the model undergoes some parameter changes. Sensitivity analysis is particularly needed when the parameters of the model cannot be estimated accurately. In these cases, it is important to study the behavior of the optimum solution in the neighborhood of the estimated parameters.

We put a lot of emphasis on this phase. And major part of each OR/MS journal is occupied by this step alone.

> **Model validity** checks whether or not the proposed model does what it purports to do — that is, does it predict adequately the behavior of the system under study? Initially, the OR team should be convinced that the models output does not include "surprises" In other words, does the solution make sense? Are the results intuitively

acceptable? On the formal side, a common method for checking the validity of a model is to compare its output with historical output data. The model is valid if, under similar input conditions, it reasonably duplicates past performance. Generally, however, there is no assurance that future performance will continue to duplicate past behavior. Also, because the model is usually based on careful examination of past data, the proposed comparison is usually favorable. If the proposed model represents a new (nonexisting) system, no historical data would be available. In such cases, we may use simulation as an independent tool for verifying the output of the mathematical model.

If we use simulation to validate the model, do we use the same simulation model which we construct in the second phase? Then the validation may be questionable.

Implementation of the solution of a validated model involves the translation of the results into understandable operating instructions to be issued to the people who will administer the recommended system. The burden of this task lies primarily with the OR team.

Even though the description of the phase is shortest, the actual process may involve a lot of time, and effort.

2.2 Winston

Winston (2003) starts a new section titled "The Seven-Step Model-Building Process" in the first chapter of page 7. His PS phases seems most up-to-date. After he explains each step in the section using an example, he lists four other exmples to illustrate the application of his model building steps.

Step 1: Formulate the Problem The operations researcher first defines the organizations problem. Defining the problem includes specifying the organizations objectives and the parts of the organization that must be studied before the problem can be solved.

He is cautious in formulating the problem as we can seet it in the second paragraphs.

Step 2: Observe the System Next, the operations researcher collects data to estimate the value of parameters that affect the organizations problem. These estimates are used to develop (in step 3) and evaluate (in step 4) a mathematical model of the organizations problem.

This observation step is one unique feature of Winston's procedure.

Step 3: Formulate a Mathematical Model of the Problem In this step, the operations researcher develops a mathematical model of the problem. In this book, we will describe many mathematical techniques that can be used to model systems.

Step 4: Verify the Model and Use the Model for Prediction The operations researcher now tries to determine if the mathematical model developed in step 3 is an accurate representation of reality. Even if a model is valid for the current situation, we must be aware of blindly applying it.

Step 5: Select a Suitable Alternative Given a model and a set of alternatives, the operations researcher now chooses the alternative that best meets the organizations objectives. (There may be more than one!)

Step 6: Present the Results and Conclusion of the Study to the Organization In this step, the operations researcher presents the model and recommendation

> from step 5 to the decision-making individual or group. In some situations, one might present several alternatives and let the organization choose the one that best meets its needs. After presenting the results of the operations research study, the analyst may find that the organization does not approve of the recommendation. This may result from incorrect definition of the organizations problems or from failure to involve the decision maker from the start of the project. In this case, the operations researcher should return to step 1, 2, or 3.

Winston describes here another unique feature of "feedback" in the latter half of the Step 6.

> **Step 7: Implement and Evaluate Recommendations** If the organization has accepted the study, then the analyst aids in implementing the recommendations. The system must be constantly monitored (and updated dynamically as the environment changes) to ensure that the recommendations enable the organization to meet its objectives.

2.3 Hillier and Lieberman

Hillier and Lieberman (2001) originally writes the first edition of the book in 1967. They have a whole second chapter titled "Overview of the Operations Research Modeling Approach". Heavy emphasis is placed on the use computer in comparison with others. They have attached an example to each of six steps, and have provided ten references at the end of the chapter.

They overview the MPSS in perspective (Hillier and Lieberman, 2011, page 7).

> The bulk of this book is devoted to the mathematical methods of operations research (OR). This is quite appropriate because these quantitative techniques form the main part of what is known about OR. However, it does not imply that practical OR studies are primarily mathematical exercises. As a matter of fact, the mathematical analysis often represents only a relatively small part of the total effort required.
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> One way of summarizing the usual (overlapping) phases of an OR study is the following:
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> **1.** Define the problem of interest and gather relevant data.
> **2.** Formulate a mathematical model to represent the problem.
> **3.** Develop a computer-based procedure for deriving solutions to the problem from the model.
> **4.** Test the model and refine it as needed.
> **5.** Prepare for the ongoing application of the model as prescribed by management.
> **6.** Implement.

They comment that these steps are described not demarcated clearly. They do not cover what is unknown, i.e. non-mathematical techniques. And these qualitative parts of OR/MS is not well-known in science. They stress on the use of compute in various steps.

The first step: "Defining the Problem and Gathering Data" is (Hillier and Lieberman, 2011, page 7):

> In contrast to textbook examples, most practical problems encountered by OR teams are initially described to them in a vague, imprecise way. Therefore, the first order of business is to study the relevant system and develop a well-defined statement of the problem to be considered. This includes determining such things as the appropriate objectives, constraints on what can be done, interrelationships between the area to be studied and other areas of the organization, possible alternative courses of action, time

limits for making a decision, and so on. This process of problem definition is a crucial one because it greatly affects how relevant the conclusions of the study will be. It is difficult to extract a “right” answer from the “wrong” problem!

The first thing to recognize is that an OR team is normally working in an *advisory capacity.* The team members are not just given a problem and told to solve it however they see fit. Instead, they are advising management (often one key decision maker). The team performs a detailed technical analysis of the problem and then presents recommendations to management. Frequently, the report to management will identify a number of alternatives that are particularly attractive under different assumptions or over a different range of values of some policy parameter that can be evaluated only by management (e.g., the trade-off between *cost* and *benefits*). Management evaluates the study and its recommendations, takes into account a variety of intangible factors, and makes the final decision based on its best judgment. Consequently, it is vital for the OR team to get on the same wavelength as management, including identifying the “right” problem from managements viewpoint, and to build the support of management for the course that the study is taking.

Ascertaining the *appropriate objectives* is a very important aspect of problem definition. To do this, it is necessary first to identify the member (or members) of management who actually will be making the decisions concerning the system under study and then to probe into this individuals thinking regarding the pertinent objectives. (Involving the decision maker from the outset also is essential to build her or his support for the implementation of the study.)

By its nature, OR is concerned with the welfare of the *entire organization* rather than that of only certain of its components. An OR study seeks solutions that are optimal for the overall organization rather than suboptimal solutions that are best for only one component. Therefore, the objectives that are formulated ideally should be those of the entire organization. However, this is not always convenient. Many problems primarily concern only a portion of the organization, so the analysis would become unwieldy if the stated objectives were too general and if explicit consideration were given to all side effects on the rest of the organization. Instead, the objectives used in the study should be as specific as they can be while still encompassing the main goals of the decision maker and maintaining a reasonable degree of consistency with the higher-level objectives of the organization.

For profit-making organizations, one possible approach to circumventing the problem of suboptimization is to use *long-run profit maximization* (considering the time value of money) as the sole objective. The adjective *long-run* indicates that this objective provides the flexibility to consider activities that do not translate into profits *immediately* (e.g., research and development projects) but need to do so *eventually* in order to be worth-while. This approach has considerable merit. This objective is specific enough to be used conveniently, and yet it seems to be broad enough to encompass the basic goal of profit-making organizations. In fact, some people believe that all other legitimate objectives can be translated into this one.

However, in actual practice, many profit-making organizations do not use this approach. A number of studies of U.S. corporations have found that management tends to adopt the goal of *satisfactory profits,* combined with *other objectives,* instead of focusing on long-run profit maximization. Typically, some of these *other* objectives might be to maintain stable profits, increase (or maintain) ones share of the market, provide for product diversification, maintain stable prices, improve worker morale, maintain family control of the business, and increase company prestige. Fulfilling these objectives might achieve long-run profit maximization, but the relationship may be sufficiently obscure that it may not be convenient to incorporate them all into this one objective.

Furthermore, there are additional considerations involving social responsibilities that are distinct from the profit motive. The five parties generally affected by a business firm located in a single country are (1) the *owners* (stockholders, etc.), who desire profits (dividends, stock appreciation, and so on); (2) the *employees,* who desire steady employment at reasonable wages; (3) the *customers,* who desire a reliable product at a reasonable price; (4) the *suppliers,* who desire integrity and a reasonable selling price for their goods; and (5) the *government* and hence the *nation*, which desire payment of fair taxes and consideration of the national interest. All five parties make essential contributions to the firm, and the firm should not be viewed as the exclusive servant of any one party for the exploitation of others. By the same token, international corporations acquire additional obligations to follow socially responsible practices. Therefore, while granting that managements prime responsibility is to make profits (which ultimately benefits all five parties), we note that its broader social responsibilities also must be recognized.

OR teams typically spend a surprisingly large amount of time *gathering relevant data* about the problem. Much data usually are needed both to gain an accurate understanding of the problem and to provide the needed input for the mathematical model being formulated in the next phase of study. Frequently, much of the needed data will not be available when the study begins, either because the information never has been kept or because what was kept is outdated or in the wrong form. Therefore, it often is necessary to install a new computer-based *management information system* to collect the necessary data on an on-going basis and in the needed form. The OR team normally needs to enlist the assistance of various other key individuals in the organization to track down all the vital data. Even with this effort, much of the data may be quite "soft," i.e., rough estimates based only on educated guesses. Typically, an OR team will spend considerable time trying to improve the precision of the data and then will make do with the best that can be obtained.

The PI phase description of Hillier, and Lieberman consists of:

- Problem description: They stress the importance of PI.
- Management perspective of a problem
- Establishing objectives
- Corporate social responsibility (CSR)
- Data collection

They emphasize the importance of obtaining "right" problem. We are biased to identify the similar problem which we encountered before. Also we are inclined to find a symptom rather than cause of a problem. For whom do we identify the problem? The management may want a specific problem which they like. Upper management, and operating managemnet may have different thought about PI. Then if the top management is bad, we may make the problem worse. thus it is clearly against the concept of corporate social responsibility, the long-term general interest of the organization.

They treat CSR very naive. In some business schools, CSR coverage is two courses or more. Our best recommendation in starting to discuss CSR is written by Friedman (1970). We do not feel CSR is the topic covered in a pair of paragraphs in the introductory OR/MS textbook.

The second step: "Formulation a Mathematical Model" is (Hillier and Lieberman, 2011, page 10):

> After the decision makers problem is defined, the next phase is to reformulate this problem in a form that is convenient for analysis. The conventional OR approach for doing this is to construct a mathematical model that represents the essence of the problem. Before discussing how to formulate such a model, we first explore the nature of models in general and of mathematical models in particular.
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> Models, or idealized representations, are an integral part of everyday life. Common examples include model airplanes, portraits, globes, and so on. Similarly, models play an important role in science and business, as illustrated by models of the atom, models of genetic structure, mathematical equations describing physical laws of motion or chemical reactions, graphs, organizational charts, and industrial accounting systems. Such models are invaluable for abstracting the essence of the subject of inquiry, showing interrelationships, and facilitating analysis.
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> Mathematical models are also idealized representations, but they are expressed in terms of mathematical symbols and expressions. Such laws of physics as $F = ma$ and $E = mc^2$ are familiar examples. Similarly, the mathematical model of a business problem is the system of equations and related mathematical expressions that describe the essence of the problem. Thus, if there are n related quantifiable decisions to be made, they are represented as **decision variables** (say, $x_1, x_2, ..., x_n$) whose respective values are to be determined. The appropriate measure of performance (e.g., profit) is then expressed as a mathematical function of these decision variables (for example, $P = 3x_1 + 2x_2 + ... + 5x_n$). This function is called the **objective function.** Any restrictions on the values that can be assigned to these decision variables are also expressed mathematically, typically by means of inequalities or equations (for example, $x_1 + 3x_1x_2 + 2x_2 \leq 10$). Such mathematical expressions for the restrictions often are called **constraints.** The constants (namely, the coefficients and right-hand sides) in the constraints and the objective function are called the **parameters** of the model. The mathematical model might then say that the problem is to choose the values of the decision variables so as to maximize the objective function, subject to the specified constraints. Such a model, and minor variations of it, typifies the models used in OR.
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> Determining the appropriate values to assign to the parameters of the model (one value per parameter) is both a critical and a challenging part of the model-building process. In contrast to textbook problems where the numbers are given to you, determining parameter values for real problems requires *gathering relevant data.* As discussed in the preceding section, gathering accurate data frequently is difficult. Therefore, the value assigned to a parameter often is, of necessity, only a rough estimate. Because of the uncertainty about the true value of the parameter, it is important to analyze how the solution derived from the model would change (if at all) if the value assigned to the parameter were changed to other plausible values. This process is referred to as **sensitivity analysis,** as discussed further in the next section (and much of Chap. 6).
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> Although we refer to "the" mathematical model of a business problem, real problems normally don't have just a single "right" model. Section 2.4 will describe how the process of testing a model typically leads to a succession of models that provide better and better

representations of the problem. It is even possible that two or more completely different types of models may be developed to help analyze the same problem.

You will see numerous examples of mathematical models throughout the remainder of this book. One particularly important type that is studied in the next several chapters is the **linear programming model,** where the mathematical functions appearing in both the objective function and the constraints are all linear functions. In the next chapter, specific linear programming models are constructed to fit such diverse problems as determining (1) the mix of products that maximizes profit, (2) the design of radiation therapy that effectively attacks a tumor while minimizing the damage to nearby healthy tissue, (3) the allocation of acreage to crops that maximizes total net return, and (4) the combination of pollution abatement methods that achieves air quality standards at minimum cost.

Mathematical models have many advantages over a verbal description of the problem. One advantage is that a mathematical model describes a problem much more concisely. This tends to make the overall structure of the problem more comprehensible, and it helps to reveal important cause-and-effect relationships. In this way, it indicates more clearly what additional data are relevant to the analysis. It also facilitates dealing with the problem in its entirety and considering all its interrelationships simultaneously. Finally, a mathematical model forms a bridge to the use of high-powered mathematical techniques and computers to analyze the problem. Indeed, packaged software for both personal computers and main-frame computers has become widely available for solving many mathematical models.

However, there are pitfalls to be avoided when you use mathematical models. Such a model is necessarily an abstract idealization of the problem, so approximations and simplifying assumptions generally are required if the model is to be *tractable* (capable of being solved). Therefore, care must be taken to ensure that the model remains a valid representation of the problem. The proper criterion for judging the validity of a model is whether the model predicts the relative effects of the alternative courses of action with sufficient accuracy to permit a sound decision. Consequently, it is not necessary to include unimportant details or factors that have approximately the same effect for all the alternative courses of action considered. It is not even necessary that the absolute magnitude of the measure of performance be approximately correct for the various alternatives, provided that their relative values (i.e., the differences between their values) are sufficiently precise. Thus, all that is required is that there be a high *correlation* between the prediction by the model and what would actually happen in the real world. To ascertain whether this requirement is satisfied, it is important to do considerable *testing* and consequent modifying of the model, which will be the subject of Sec. 2.4. Although this testing phase is placed later in the chapter, much of this *model validation* work actually is conducted during the model-building phase of the study to help guide the construction of the mathematical model.

In developing the model, a good approach is to begin with a very simple version and then move in evolutionary fashion toward more elaborate models that more nearly reflect the complexity of the real problem. This process of *model enrichment* continues only as long as the model remains tractable. The basic trade-off under constant consideration is between the *precision* and the *tractability* of the model. (See Selected Reference 6 for a detailed description of this process.)

A crucial step in formulating an OR model is the construction of the objective function. This requires developing a quantitative measure of performance relative to each

> of the decision maker's ultimate objectives that were identified while the problem was being defined. If there are multiple objectives, their respective measures commonly are then transformed and combined into a composite measure, called the **overall measure of performance.** This overall measure might be something tangible (e.g., profit) corresponding to a higher goal of the organization, or it might be abstract (e.g., utility). In the latter case, the task of developing this measure tends to be a complex one requiring a careful comparison of the objectives and their relative importance. After the overall measure of performance is developed, the objective function is then obtained by expressing this measure as a mathematical function of the decision variables. Alternatively, there also are methods for explicitly considering multiple objectives simultaneously, and one of these (goal programming) is discussed in Chap. 7.

They discuss

- Basic setup of mathematical model
- Parameter estimation
- Mathematical model in general
- How to develop model

When we discuss about parameter estimation, extreme care must be paid to avoid Hawthorne effect (Landsburger 1958). If we closely monitor the organization, its effect may be encountered; thus we may need proper physical, and psychological distance to the target to be observed. This phenomena is similar to the Uncertainty Principle in quantum phyhsics.

Also they refer "right" model in this stage. Our question to them is to whose righteousness they refer.

The third step: "Deriving Solutions from the Model" is (Hillier and Lieberman, 2011, page 14):

> A common theme in OR is the search for an **optimal,** or best, **solution.** Indeed, many procedures have been developed, and are presented in this book, for finding such solutions for certain kinds of problems. However, it needs to be recognized that these solutions are optimal only with respect to the model being used. Since the model necessarily is an idealized rather than an exact representation of the real problem, there cannot be any utopian guarantee that the optimal solution for the model will prove to be the best possible solution that could have been implemented for the real problem. There just are too many imponderables and uncertainties associated with real problems. However, if the model is well formulated and tested, the resulting solution should tend to be a good approximation to an ideal course of action for the real problem. Therefore, rather than be deluded into demanding the impossible, you should make the test of the practical success of an OR study hinge on whether it provides a better guide for action than can be obtained by other means.
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> Eminent management scientist and Nobel Laureate in economics Herbert Simon points out that **satisficing** is much more prevalent than optimizing in actual practice. In coining the term *satisficing* as a combination of the words *satisfactory* and *optimizing,* Simon is describing the tendency of managers to seek a solution that is "good enough" for the problem at hand. Rather than trying to develop an overall measure of performance to optimally reconcile conflicts between various desirable objectives (including well-established criteria for judging the performance of different segments of the

organization), a more pragmatic approach may be used. Goals may be set to establish minimum satisfactory levels of performance in various areas, based perhaps on past levels of performance or on what the competition is achieving. If a solution is found that enables all these goals to be met, it is likely to be adopted without further ado. Such is the nature of satisficing.

The distinction between optimizing and satisficing reflects the difference between theory and the realities frequently faced in trying to implement that theory in practice. In the words of one of England's OR leaders, Samuel Eilon, "Optimizing is the science of the ultimate; satisficing is the art of the feasible."

OR teams attempt to bring as much of the "science of the ultimate" as possible to the decision-making process. However, the successful team does so in full recognition of the overriding need of the decision maker to obtain a satisfactory guide for action in a reasonable period of time. Therefore, the goal of an OR study should be to conduct the study in an optimal manner, regardless of whether this involves finding an optimal solution for the model. Thus, in addition to pursuing the science of the ultimate, the team should also consider the cost of the study and the disadvantages of delaying its completion, and then attempt to maximize the net benefits resulting from the study. In recognition of this concept, OR teams occasionally use only **heuristic procedures** (i.e., intuitively designed procedures that do not guarantee an optimal solution) to find a good **suboptimal solution.** This is most often the case when the time or cost required to find an optimal solution for an adequate model of the problem would be very large. In recent years, great progress has been made in developing efficient and effective heuristic procedures (including so-called metaheuristics), so their use is continuing to grow.

The discussion thus far has implied that an OR study seeks to find only one solution, which may or may not be required to be optimal. In fact, this usually is not the case. An optimal solution for the original model may be far from ideal for the real problem, so additional analysis is needed. Therefore, **postoptimality analysis** (analysis done after finding an optimal solution) is a very important part of most OR studies. This analysis also is sometimes referred to as **what-if analysis** because it involves addressing some questions about *what* would happen to the optimal solution *if* different assumptions are made about future conditions. These questions often are raised by the managers who will be making the ultimate decisions rather than by the OR team.

The advent of powerful spreadsheet software now has frequently given spreadsheets a central role in conducting postoptimality analysis. One of the great strengths of a spreadsheet is the ease with which it can be used interactively by anyone, including managers, to see what happens to the optimal solution when changes are made to the model. This process of experimenting with changes in the model also can be very helpful in providing understanding of the behavior of the model and increasing confidence in its validity.

In part, postoptimality analysis involves conducting **sensitivity analysis** to determine which parameters of the model are most critical (the "sensitive parameters") in determining the solution. A common definition of *sensitive parameter* (used throughout this book) is the following.

> For a mathematical model with specified values for all its parameters, the model's **sensitive parameters** are the parameters whose value cannot be changed without changing the optimal solution.

Identifying the sensitive parameters is important, because this identifies the parameters

> whose value must be assigned with special care to avoid distorting the output of the model.
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> The value assigned to a parameter commonly is just an *estimate* of some quantity (e.g., unit profit) whose exact value will become known only after the solution has been implemented. Therefore, after the sensitive parameters are identified, special attention is given to estimating each one more closely, or at least its range of likely values. One then seeks a solution that remains a particularly good one for all the various combinations of likely values of the sensitive parameters.
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> If the solution is implemented on an ongoing basis, any later change in the value of a sensitive parameter immediately signals a need to change the solution.
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> In some cases, certain parameters of the model represent policy decisions (e.g., resource allocations). If so, there frequently is some flexibility in the values assigned to these parameters. Perhaps some can be increased by decreasing others. Postoptimality analysis includes the investigation of such trade-offs.
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> In conjunction with the study phase discussed in the next section (testing the model), postoptimality analysis also involves obtaining a sequence of solutions that comprises a series of improving approximations to the ideal course of action. Thus, the apparent weaknesses in the initial solution are used to suggest improvements in the model, its input data, and perhaps the solution procedure. A new solution is then obtained, and the cycle is repeated. This process continues until the improvements in the succeeding solutions become too small to warrant continuation. Even then, a number of alternative solutions (perhaps solutions that are optimal for one of several plausible versions of the model and its input data) may be presented to management for the final selection. As suggested in Sec. 2.1, this presentation of alternative solutions would normally be done whenever the final choice among these alternatives should be based on considerations that are best left to the judgment of management.

They emphasize that the solution derived from the model is only optimal to the model, not to the actual solution of the real situation. They place a proper perspective of the solution obtained from the model.

Then they discuss "satisficing" (Simon 1976), and post-optimality analysis including sensitivity analysis. They are optimist in parameter estimation confessing that eact value will be known after implementation. We feel they do not understand the Hawthorn effect at all.

The fourth step: "Testing the Model" is (Hillier and Lieberman, 2011, page 16):

> Developing a large mathematical model is analogous in some ways to developing a large computer program. When the first version of the computer program is completed, it inevitably contains many bugs. The program must be thoroughly tested to try to find and correct as many bugs as possible. Eventually, after a long succession of improved programs, the programmer (or programming team) concludes that the current program now is generally giving reasonably valid results. Although some minor bugs undoubtedly remain hidden in the program (and may never be detected), the major bugs have been sufficiently eliminated that the program now can be reliably used.
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> Similarly, the first version of a large mathematical model inevitably contains many flaws. Some relevant factors or interrelationships undoubtedly have not been incorporated into the model, and some parameters undoubtedly have not been estimated correctly. This is inevitable, given the difficulty of communicating and understanding all the aspects and subtleties of a complex operational problem as well as the difficulty of collecting reliable data. Therefore, before you use the model, it must be thoroughly

tested to try to identify and correct as many flaws as possible. Eventually, after a long succession of improved models, the OR team concludes that the current model now is giving reasonably valid results. Although some minor flaws undoubtedly remain hidden in the model (and may never be detected), the major flaws have been sufficiently eliminated that the model now can be reliably used.

This process of testing and improving a model to increase its validity is commonly referred to as **model validation.**

It is difficult to describe how model validation is done, because the process depends greatly on the nature of the problem being considered and the model being used. However, we make a few general comments, and then we give some examples. (See Selected Reference 2 for a detailed discussion.)

Since the OR team may spend months developing all the detailed pieces of the model, it is easy to "lose the forest for the trees." Therefore, after the details ("the trees") of the initial version of the model are completed, a good way to begin model validation is to take a fresh look at the overall model ("the forest") to check for obvious errors or oversights. The group doing this review preferably should include at least one individual who did not participate in the formulation of the model. Reexamining the definition of the problem and comparing it with the model may help to reveal mistakes. It is also useful to make sure that all the mathematical expressions are *dimensionally* consistent in the units used. Additional insight into the validity of the model can sometimes be obtained by varying the values of the parameters and/or the decision variables and checking to see whether the output from the model behaves in a plausible manner. This is often especially revealing when the parameters or variables are assigned extreme values near their maxima or minima.

A more systematic approach to testing the model is to use a **retrospective test.** When it is applicable, this test involves using historical data to reconstruct the past and then determining how well the model and the resulting solution would have performed if they had been used. Comparing the effectiveness of this hypothetical performance with what actually happened then indicates whether using this model tends to yield a significant improvement over current practice. It may also indicate areas where the model has shortcomings and requires modifications. Furthermore, by using alternative solutions from the model and estimating their hypothetical historical performances, considerable evidence can be gathered regarding how well the model predicts the relative effects of alternative courses of actions.

On the other hand, a disadvantage of retrospective testing is that it uses the same data that guided the formulation of the model. The crucial question is whether the past is truly representative of the future. If it is not, then the model might perform quite differently in the future than it would have in the past.

To circumvent this disadvantage of retrospective testing, it is sometimes useful to continue the status quo temporarily. This provides new data that were not available when the model was constructed. These data are then used in the same ways as those described here to evaluate the model.

Documenting the process used for model validation is important. This helps to increase confidence in the model for subsequent users. Furthermore, if concerns arise in the future about the model, this documentation will be helpful in diagnosing where problems may lie.

To perform a retrospective test properly, simple hadling of historical data should be avoided to construct a model, and to validate it. One proper way is to divide the historical data into two groups randomly from the beginning. Then one group is emplyed to construct a model, and another is tested to validate it.

The fifth step: "Preparing to Apply the Model" is (Hillier and Lieberman, 2011, page 18):

> What happens after the testing phase has been completed and an acceptable model has been developed? If the model is to be used repeatedly, the next step is to install a well-documented *system* for applying the model as prescribed by management. This system will include the model, solution procedure (including postoptimality analysis), and operating procedures for implementation. Then, even as personnel changes, the system can be called on at regular intervals to provide a specific numerical solution.
>
> This system usually is *computer-based.* In fact, a considerable number of computer programs often need to be used and integrated. *Databases and management information systems* may provide up-to-date input for the model each time it is used, in which case interface programs are needed. After a solution procedure (another program) is applied to the model, additional computer programs may trigger the implementation of the results automatically. In other cases, an *interactive* computer-based system called a **decision support system** is installed to help managers use data and models to support (rather than replace) their decision making as needed. Another program may generate *managerial reports* (in the language of management) that interpret the output of the model and its implications for application.
>
> In major OR studies, several months (or longer) may be required to develop, test, and install this computer system. Part of this effort involves developing and implementing a process for maintaining the system throughout its future use. As conditions change over time, this process should modify the computer system (including the model) accordingly.

The sixth step: "Implementation" (Hillier and Lieberman, 2011, page 20):

> After a system is developed for applying the model, the last phase of an OR study is to implement this system as prescribed by management. This phase is a critical one because it is here, and only here, that the benefits of the study are reaped. Therefore, it is important for the OR team to participate in launching this phase, both to make sure that model solutions are accurately translated to an operating procedure and to rectify any flaws in the solutions that are then uncovered.
>
> The success of the implementation phase depends a great deal upon the support of both top management and operating management. The OR team is much more likely to gain this support if it has kept management well informed and encouraged managements active guidance throughout the course of the study. Good communications help to ensure that the study accomplishes what management wanted and so deserves implementation. They also give management a greater sense of ownership of the study, which encourages their support for implementation.
>
> The implementation phase involves several steps. First, the OR team gives operating management a careful explanation of the new system to be adopted and how it relates to operating realities. Next, these two parties share the responsibility for developing the procedures required to put this system into operation. Operating management then sees that a detailed indoctrination is given to the personnel involved, and the new course of action is initiated. If successful, the new system may be used for years to come. With this in mind, the OR team monitors the initial experience with the course of action taken and seeks to identify any modifications that should be made in the future.

Throughout the entire period during which the new system is being used, it is important to continue to obtain feedback on how well the system is working and whether the assumptions of the model continue to be satisfied. When significant deviations from the original assumptions occur, the model should be revisited to determine if any modifications should be made in the system. The postoptimality analysis done earlier (as described in Sec. 2.3) can be helpful in guiding this review process.

Upon culmination of a study, it is appropriate for the OR team to *document* its methodology clearly and accurately enough so that the work is *reproducible. Replicability* should be part of the professional ethical code of the operations researcher. This condition is especially crucial when controversial public policy issues are being studied.

2.4 Wagner

Wagner (1969) classifies one plus four step method. Since the quoted edition is the oldest among the OR/MS books we cited, it has a good flavor of classic PS step.

A prelude to a quantitative analysis of a decision problem should be a thorough qualitative analysis. This initial diagnostic phase aims at identifying what seem to be the critical factors — of course, subsequent analysis may demonstrate that some of these factors are not actually so significant as they first appear. In particular, it is important to attain a preliminary notion of what the principal decisions are, what the measures of effectiveness are among these choices, and what sorts of tradeoffs among these measures are likely to ensue in a comparison of the alternatives. There will be trouble ahead unless you get a good "feel" for the way the problem is viewed by the responsible decision-makers. Without this appreciation, you may encounter considerable difficulty in gaining acceptance and implementing your findings. What is worse, your results could very well be erroneous or beside the point.

Formulating the problem. The preceeding diagnostic should yield a statement of the problem's elements. These include the controllable or decision variables, the uncontrollable variables, the restrictions or constraints on the variables, and the objectives for defining a good or improved solution.

In the formulation process, you must establish the confines of the analysis. Managerial decision-making problems typically have multifold impacts, some of them immediate and others remote (although perhaps equally significant). Determining the limits of a particular analysis is mostly a matter of judgement.

Building the model. Here is where you get down to the fine detail. You must decide on the proper data inputs and design the appropriate information outputs. You have to identify both the static and dynamic structural elements, and devise mathematical formulas to represent the interrelationships among these elements. Some of these interdependencies may be posed in terms of constraints or restrictions on the variables. Some may take the form of a probabilistic evolutionary system.

You also must choose a time horizon (possibly the "never-ending future") to evaluate the selected measure of effectiveness for the various decisions. The choice of this horizon in turn influences the nature of the constraints imposed, since, with a long enough horizon, it is usually possible to remove any short-run restrictions by an expenditure of resources.

Performing the analysis. Given the initial model, along with its parameters as specified by historical, technological, and judgmental data, you next calculate a mathematical solution. Frequently, a solution means values for the decision variables that optimize one of the objectives. The various mathematical techniques for arriving at solutions comprise much of the contents of this text.

As pointed out previously, if the formulation of the model is too complex and too detailed, then the computational task may surpass the capabilities of present-day computers. If the formulation is too simple, the solution may be patently unrealistic. Therefore, you can expect to redo some of the steps in the formulation, model-building, and analysis phasees, until you obtain satisfactory results.

A major part of the anlysis consists of determining the sensitivity of the solution to the model specification, and in particular to the accuracy of the input data and structural assumptions. Because sensitivity testing is so essential a part of the validation process, you must be careful to build your model in such a way as to make this process computationally tractable.

Implementing the findings and updating the model. Unfortunately, most tyro management scientists fail to realize the implementation begins on the very first day of an operations research project. There is no "moment of truth" when the analyst states, "Here are my results," and the manager replies, "Aha! Now I fully understand. Thanks for giving me complete assurance about the correct decision."

We consider the entire process of implementation in Chap.22. But we mention here the importance of having those executives who must act on the findings participate on the team that analyze the problem. Otherwise, the odds are heavy that the project will be judged only as a provocative, but inconclusive, exercise.

It is common for an operations research model to be used repeatedly in the analysis of decision problems. Each time, the model must be revised to take account of both the specifics of the problem and current data. A good practitioner of operations research realizes that his model may have a long life, and so documents its details as well as plans for its updating.

2.5 Polya

Polya (2004) originally writes its first edition of the book in 1945 without any reference materials. He analyzes mathematical problem solving process, and develops his four-step process: We believe his alogorithmic problem solving process is inherited by OR/MS; thus it is important to quote bellow.

Understanding the Problem

First. You have to *understand* the problem.

What is the unknow? What are the data? What is the condition?
Is it possible to satisfy the condition? Is the condition sufficient to determine the unknown? Or is it insufficient? Or redundant? Or contradictory?
Draw a figure. Introduce suitable notation.
Separate the various parts of condition. Can you write them down?

Devise a Plan

Second. Find the connection between the data and the unknown. You may be obliged to consider auxiliary problems if an immediate connection cannot be found. You should obtain eventaully a *plan* of the solution.

Have you seen it before? Or have you seen the same problem in a slightly different form?
Do you know a related problem? Do you know a theorem that could be useful?
Look at the unknown! And try to think of a familiar problem having same or similar unknown.
Here is a problem related to yours and solved before. Could you use it? Could you use its result? Could you use its method? Should you use some auxiliary element in order to make its use possible?
Could you restate the problem? Could you still restate it differently? Goback to definitions.
If you cannot solve the proposed problemtry to solve first some related problem. Could you imaginea more accessible related problem? A more general problem? A more special problem? An analogous problem? Could you solve a part of the problem? Keep only a part of condition, drop the other part; how far is the unknown then determined, how can it vary? Could you derive something useful from the data? could you think of other data appropriate to determine the unknown? could you change the unknown or the data, or both if necessary, so that the new unknown and the new data are nearer to each other?
Did you use all the data? Did you use the whole condition? Have you taken into account all essential notions involved in the problem?

Carrying out the Plan

Third. *Carry out* you plan.

Carrying out your plan of the solution, *check each step.* Can you see clearly that the step is correct? Can you prove that it is correct?

Looking back

Fourth. *Examine* the solution obtained.

Can you *check the result?* Can you check the argument?
Can you derive the result differently? Can you see it at a glance?
Can you use the result, or the method, for some other problem?

2.6 Summary table

We will sum up this section by presenting a table comparing each author's steps.

Taha	Winston	Hillier	Wagner
Def. of the prob.	Form. the Prob. Obs. the System	Def. the prob.	Identification
Const. of the model	Form. a Model	Form. a Model	Form. a Model Build. the model
Sol. of the model Valid. of the model	Verify the Model	Develop a proc. Test the model	Perform. the anal.
Implementation	Select an Alt. Presentation Implementation	Prepare to apply Implementation	Implement

- The general direction for the PS is the same.
- In the middle of all steps, there exists the common step of “Formulate a model” (Construction of the model).
- The final step is the same: ”Implementation”.

3. Properties of Managerial Problem-solving

Some dimensions of Managerial PS we need to consider are:

- Structured, and Unstructured problem. Only classroom type of problem is well structured, and most of the real world problems are unstructured.
- Closed, and Open systems. Most of the problem we have solved belong to closed system, or an open system whose input, and output to/from the supra-system is well-balanced.
- Static, and Dynamics.
- Recurrent, and Non-recurrent, or difficult to replicate process. One time only, or only rarely observed events are difficult to manage.
- Reversible, and irreversible.

Needless to say the combination of the latter one is most difficult to approach. Most textbook example is the combination of the former ones; thus rather easy to model it.

Some of characteristics of Managerial PS are.

- Incomplete, imperfect, varying accuracy of data
- Inter-dependencies or connectedness
- Multi-goals
- Impacts on people involved

If too many people are involved, it can be easily classified to a political problem like “too big to fail”, or automobile industry in the State because it covers a lot of people.

4. Difficulties in Problem Identification

If we can identify the problem properly, we can say we are half done at our MPSS. Next major part of MPSS is implementation stage which we do not discuss in this paper.

Some of mistakes involving PI lie:

- Time span of data collection, and decision involvement
- Location
- Assumptions
- Skill level of operator

Impacts of Eastern Japan quake on the First Fukushima Nuclear Plant on March 11th, 2011 presents a good case study. It is a typical application of OR, but we have failed to all of the above.

- Data collection ignores major historic quake, and tsunami broke out around the site.
- The site original shape has destroyed by excavating the cliff to invite tsunami attack.
- The on-site-operator did not know what to do in crisis.

We have to point out that the Second Fukushima Nuclear Plant, operated by the same operator: Tokyo Electric Power Company (TEPCO), and situated nearby the First, has survived the quake, and tsunami on the same date.

Top management may target the PI to gear the organization's specific needs to be achieved; thus the recommendation may lead to change of product mix. And reallocation of resources leads to a specific plant shutdown.

PI may be technically incorrect due to the incompetence of operations researchers, or due to the fact that there is simply not good technology. Or the process of problem identification is simply politically infeasible. Management leadership may determine the PI. Thus it may be a political process, rather than scientific.

People who are involved in PI are: management, and operations researchers. The actual symptoms may be recognized at the lowest level of management due to technical difficulties. Upper management may exercise its power to develop it as a real PI.

PI may be erroneous due to:

- Politically, or environmentally incorrect. For example, criticizing upper management from lower management.
- Economically incorrect. Money alone does not justify
- Technically incorrect Technology is unreliable

Some issue involved in PI are:

- Mis-identification
  - Case: Avalon machinery Independent demand Dependent demand Supply chain
  - Case: Fukushima Daiichi Nuclear Plant Creation of "myth of nuclear plant safety": Nothing dangerous happens; thus no need to prepare
    * Facility location: Geopolitical problem
    * Method of construction: Destroy 30∼35 meter high plateau, and make the site easily accessible from sea
    * Accident problem: Hierarchical problem
      1. Long term problem: Contaminated materials, Radioactive waste
      2. Mid range problem: Properly decommissioning nuclear reactors
      3. Short run problem: Contaminated water

  Solving wrong problem with extremely difficult & sensitive method

  Solving symptoms rather the root of the problem
- Different Organizational views: Depending of the organizational level, and Different informal interest groups within the organization.
- Organizationally acceptable problems: Even the true problem is upper management, pointing finger at them never solve the problem.

- Scope of problem: Position the problem in appropriate level in the organization, for the successful consultant business. But you know it does not solve the problem. Even it may creates another problems in the future. Is it OK to try to solve the problem which may be root of the problem, but violates organizational rank.

- Duration of problem: Are we dealing about this quarter, semi-year, year?

General problem may be acceptable; but going into specifics of problem creates differences. Profit maximizing may be acceptable, but going to revenue maximization, and/or cost minimization may create problem.

Using heuristics, rules of thumbs, and choosing "do as we did previously" are nothing wrong at all due to our bounded rationality, and limited resources.

Fail-safe is an important feature of the choice involved. Nuclear power plant is not fail-safe at all at the present day's technology. It can be safe enough in the East coast of the State, but it has not been safe enough in Japan due to frequent "acts of God": quakes, volcano eruptions, and tsunami (which originates Japanese language meaning great tidal wave).

Identified problem must be consistent with long-run firm's objective, and middle-run firm's plan. Operations researchers are good at solving short-run problem. Here the physical duration of time depends on the industry. For example, two to three year period can be short-run for the electrical power supply company, and one century or so is long-run. Sometimes a short-run problem is simply a manifestation symptom of underlying and hidden middle-run problem of the firm; thus one we solve one symptom, then another will pop up.

For example, a section manager reports to a department manager. Most of the section manager tasks involves the decision making resulting "Do nothing" or, do as done previously. Now some operational difficulties arise in the section. Then an operations researcher hired by the department head comes in, and telling the section manager to modify one of his task decision making.

The manager forces himself to satisficing behavior rather than optimal due to bounded rationality, restricted resources, limited responsibility, and so on (Simon 1976, Takahashi 2015). Thus if nothing detrimental events occurs, he will not change his decision-making behavior. Therefore only these operational difficulties may justify his decision-making pattern.

5. Conclusion

We need to develop a procedure to identify the problem. Apply these steps themselves to the each step of the problem-solving until we reach to our desired level of granuity. If we are allowed to use Polya's terminology, each step should be labeled somewhat like the followings:

1. How to identify the problem.

2. How to formulate the problem to a model

3. How to solve it.

4. How to validate it.

5. How to implement it.

We have developed some skills to deal with these middle steps. And Hillier and Lieberman details for each step using a whole one chapter; thus its description is the good basis to develop the substeps. Some people may posses an excellent skills in execution through experiences. We are very immature to identify the problem because most of OR/MS problem in class is well identified ready to be solved in short time.

Most of the manager of the organization do not utilize the techniques of OR/MS, and choose "do nothing", or "do just like before". Why is it? Managers focus on problematic area, and they pay less attention to other tasks. Can we believe managers to apply formal OR/MS techniques to all of his tasks? If they are good techniques, why we do not?

Studying managerial decision making cases, and acquiring analytical tools are make an inseparable skill. Each skill has to be an true expert in OR/MS. Sadly we seem to be good at analytical skills only.

Document failed projects. Most organization has a full of failed projects. Some of the financially failed case can be found in the bankruptcy; but they do not necessary mean money is the cause of the failure. Some of the well-documented historical projects which one is termed success, and another is failure are:

- Amensen, and Scott South Pole expeditions
- Mount Hakkohda: One group of selected several men from a Imperial Japanese Army infantry regiment, and another group of about 200 men from a different regiment tried to traverse Mt. Hakkoda in the severe winter blizzard days of 1902 to anticipate potential war with Russia (Nitta 1992).
- The Second , and the First Fukushima Nuclear Plant in March 2011.

PI is closely related to the opportunity assessment. Failure to identify properly leads to the demerits associated to loss of opportunity.

We need to include two courses in OR/MS curriculum: Organizational Behavior, and Environment of a Firm. From the first course, we learn basic understanding what people feel, and how people get motivated in the firm. And from the second course we study the basic mechanism surrounding the firm. Just imagine an operations researcher brought in to a firm of a comparable size and business in the State, and China. Do we solve identical, or similar problem? Additionally, do we implement the recommendations in a similar fashion? We do not think so because OR/MS is a contingent theory based on the various situations. Thus in addition to the mathematical techniques, we need to learn both a supra-system: environment, and important subsystem: human organizational behavior.

Reference

Milton Friedman, "The Social Responsibility of Business is to Increase its Profits", New York Times Magazines, September 13th, 1970.

Frederick S. Hillier, and Gerald J. Lieberman, Introduction to Operations Research, Seventh edition, McGraw-Hill, New York, 2001.

Henry A. Landsberger, Hawthorne revisited, Cornell University, Ithaca, New York, 1958.

Jiro Nitta, Death March on Mount Hakkoda, Stone Bridge Press, 1992.

G. Polya, How to Solve It, Expanded Princeton Science Library Edition, Princeton University Press, Princeton, New Jersey, 2004.

Herbert A. Simon, Administrative Behavior, Third edition, Free Press, New York, New York, 1976.

Hamdy A. Taha, Operation research: an introduction, Eighth edition, Pearson Education, Upper Saddle River, New Jersey, 2007.

Nobuo Takahashi, "Where is Bounded Rationality From?", Annals of Business Administrative Science 14 (2015) 6782, Tokyo, Japan.

Harvery M. Wagner, Principles of Operations Reserach, Prentice-Hall, Englewood Ciffs, New Jersey, 1969.

Wayne L. Winston, Operations Research: Applications and Algorithms, Fourth Edition, Duxbury Press, Pacific Grove, California, 2003.