

CHAPTER 10

A Scientific Approach to Managing Hospitality Operations

Gary M. Thompson

Cornell University

This chapter illustrates why you and your organization will benefit from taking a scientific approach to managing operations. Does the phrase scientific management give you visions of a person in a white coat with thick glasses and bad hair poring over a clipboard? Well, this chapter is *not* about getting a new wardrobe, new hairstyle, new glasses, or upping your nerd quotient! (You could, however, hire someone who looks like that, I suppose.) Instead, what I discuss here is a thoughtful, careful, analytical way for you to look at operations. The idea is to apply principles of good science to the task of managing operations. You already have many managerial skills, and this chapter seeks to show you how to apply good science to the task of managing operations so that you can make even better decisions.

In this chapter I talk about what I believe is required to take a scientific approach to managing operations. That includes (1) focusing on data, (2) dealing with complexity, and (3) taking actions that are driven by rigorous analysis. To show you how this can work, I give you two fairly detailed examples—one on staffing for seasonal demand variation and the other on optimizing restaurant table mixes. As a word of warning, though, you will see some equations in this chapter! Here we go.

Good Data is a Necessity

Perhaps the most important requirement of applying science to managing operations is the availability of good data. You need accurate data to make sure your decisions are based on solid reality, rather than perceptions. Without data, you'll have to base your decisions on assumptions, but you probably won't have the information you need to fully analyze a situation. Take the time required for a housekeeper to clean a room, for example. Your hotel might be one that uses a standard, say, 30 minutes per room (which amounts to 16 rooms per day). But perhaps the housekeeper doesn't really need 30 minutes; maybe it's really 20, or maybe it's really 40. Without data, you won't really know the real time required, because you don't know if your standard took into account all of the factors that affect the length of time a housekeeper requires. A short list of the factors includes: the number of guests in the room,

the nature of the guests (adults or children, for example), whether the guests are staying over or new guests will be occupying the room, the size of the room, the number of beds, and the time of year (which affects guests' activities). So, you could use a fixed standard, but it might make more sense to collect data to determine the complete characteristics of the task. Perhaps the time standard needs to be adjusted by the season or according to the type of room.

In general, the more data you compile, the better, since the analyses that can be performed are limited to the data that are available. I know it costs money to collect data, but let me give you five reasons for why it's worth doing—and might not be as expensive as you think. First, it can often be well worth the cost of hiring some students or having existing employees spend time collecting data. This would not have to be done in perpetuity, but rather periodically. Second, you can search for inexpensive ways to collect data as a by-product of the existing operations. Third, employing technology—such as point-of-sale systems—often yields data collection opportunities in addition to operational efficiencies. Fourth, you can consider redesigning your operations to facilitate data collection. Fifth, the benefits of the data often extend beyond their original purpose. For example, the data collected on the factors influencing the time housekeepers require per room could be used for forecasting future labor requirements, rather than simply establishing appropriate standards.

Certainly, not all data are equally good, since data are often inaccurate. Correcting the inaccuracies after the fact can be a challenge. The best way to ensure accurate data, where the data are dependent on employees' actions, is to train employees about the importance of how accurate data leads to operational improvements, and to ensure that the data are used for developmental, rather than punitive, purposes. For example, a fast-food restaurant that uses a timer to measure how long customers wait to receive their meals has the potential to measure the service levels that customers experience. However, if meeting the service standard becomes the primary goal, and employees are chastised for not meeting it, then don't be surprised to see behaviors that result in inaccurate data, such as part of the service happening "off-the-clock." You'll see an excellent example in Chapter 12 of the value of collecting and using data to correct service issues, rather than to discipline employees.

Dealing with Complexity

The main reason to apply a scientific approach to managing operations is that doing so offers a means of dealing with the complexity of management decisions. Consider, for example, all the constraints and myriad idiosyncrasies related to just one of those decisions—scheduling employees. Even if you're well practiced in setting schedules, I'm sure there are still times when it's a problem to balance all the complications and to predict the outcomes in uncertain environments. Rather than take the many different operational components into account, many managers take shortcuts. Some managers use the "photocopier method" of workforce scheduling, which means that this week's schedule is simply a photocopy of last week's schedule. This saves the trouble of developing a new schedule, but it might not actually match up to the operational needs. You've probably seen the results of such suboptimal decisions when you walk into, say, a quick-service restaurant and find several employees having a wonderful chat, because there's no business.

Actions Driven by Rigorous Analysis

The third component of managing operations scientifically is taking actions based on rigorous analysis. In short, once you have data in hand, you can make powerful decisions that fit well with each situation. Having good data saves you from inadvertently making a decision that is based on a coincidental observation. As an example, where I grew up in eastern Canada, in winter, people would say: “It’s always cold when there’s a full moon.” Well, yes, typically it *is* cold on a Canadian winter night when you can see the full moon. However, the key word in this statement is *see*. It’s cold when it’s clear, and that’s when you can actually see a full moon. When there is a full moon and it’s cloudy (and consequently warmer), the moon isn’t visible. Thus, people associate full moon and cold, rather than clear and cold. But we know very well that it’s not really the moon that causes the cold night. It’s the underlying factor—clear or cloudy—that explains what’s actually happening. Now, consider a hospitality example. If I were to show you some data that indicate that hospitality companies that have more days of training per employee have lower employee turnover, what would you conclude? Is it the training that leads to reduced turnover, or are they both influenced by a third factor? Well, if you had data only on training hours and turnover, you couldn’t actually tell. Driving actions by analysis means that the data have to be extensive and the analysis has to be thorough.

Building Models from Data

An implication of driving actions by analysis is the need for model building. Building models has several benefits. First, it forces an organization to be explicit about its assumptions. This means that you can question the assumptions. Second, it allows for knowledge dissemination. Rather than all the decision-affecting factors being locked in someone’s head (with the risk of the person being run over by a bus and that knowledge lost forever), explicit models allow other people in the organization to see what factors are being considered. Thus, others can understand the business and better contribute to refining the models. Third, and perhaps most important, models are better able to deal with the complexities of decision making. In the next sections, I’ll provide two extended examples of how data analysis and model building can help with complex decisions. In both cases, you’ll see some conflict between what we think we see and what actually is happening. The first example involves optimizing the table mixes in a restaurant, and the second considers the problems of seasonal demand variability as managers try to staff a resort.

Before I give you those cases, let me mention one other example of using analysis and a model to guide decision making. This is the Wine Cellar Management Tool that I developed, which is available free from the Cornell Center for Hospitality Research (chr.cornell.edu). The tool, which is spreadsheet based, takes the guesswork out of managing a wine cellar. Essentially, it’s a sophisticated inventory management tool, a key feature of which is its ability to consider each wine’s “drinkability window,” which is the period of time that the wine is at its peak. It’s designed to help people avoid one of life’s true disappointments—drinking, past its peak, what had been a good, or even great, wine.

Example 1- Restaurant Table Mixes

The first extended example I cover concerns restaurant tables. How many times have you gone into a busy restaurant and seen lots of tables occupied but also many empty seats at those occupied tables? Those empty seats,

which occur because the restaurant is not matching its capacity to its demand, represent a missed opportunity for the restaurant. So, if a restaurant manager wanted to go about optimizing the use of the space devoted to seating customers, how would he or she approach the problem? Certainly, one approach would be trial-and-error experimentation: changing the mix a little, observing the results, locking in the change if it yielded an improvement, trying something else if it didn't. Observations could also be helpful: seeing empty seats at occupied 4-tops would suggest that the restaurant should have more 2-tops and fewer 4-tops. Implementing such a trial-and-error approach would almost certainly take a long time and the manager would probably never be confident that the restaurant had the correct mix of capacity.

Now, let's see how that manager could approach this problem scientifically. First, the manager would need some data about customer demand. If the restaurant has a point-of-sale system (a POS), then the manager could extract information on party sizes. If the restaurant does not have a POS, the manager would have to record the data manually. Let's say, for example, that the historical data for a busy period (say, dinner on Friday) was as given in Table 10.1. For the sake of this example, let's also assume that the restaurant seated parties of one and two only at 2-tops and parties of three and four at 4-tops. If the restaurant had 50 seats, how many 2-tops and how many 4-tops should it have?

A common, but incorrect answer is fifteen 2-tops and five 4-tops. The intuition behind the 15-5 answer is that adding the probabilities of parties of one and two gives 59 percent for the 2-tops. Fifty-nine percent of 50 seats is just about 30 seats, which converts to the fifteen 2-tops. Adding the probabilities of the parties of three and four gives 41 percent for the 4-tops. Forty-one percent of 50 seats is just about 20 seats, which converts to the five 4-tops. Now, let's look at why the answer of 15-5 doesn't work.

The answer lies in the fact that a party of three or four seated in a 4-top requires twice as many seats as does a party of one or two seated in a 2-top. The capacity allocation decision needs to consider more than just the likelihoods of the different party sizes—it also needs to consider the capacity required by each party. Doing so, as shown in Figure 10.1, yields eleven 2-tops and

Table 10.1
Historical Party-Size
Information for Dinner on Fridays
in a Popular Restaurant

Party Size	Percentage of Total Parties
1	8%
2	51%
3	25%
4	16%

seven 4-tops. Let's think about this for a minute: the first-blush intuition told us to use fifteen 2-tops and five 4-tops, while a more considered approach suggested

Figure 10.1
Approaching the Table Mix Problem Scientifically

This problem could be approached mathematically (i.e., scientifically). Let x = the number of 2-tops and y = the number of 4-tops. The total number of seats available for allocation would define the restriction:

$$2x + 4y = 50$$

We also know, from the probabilities of the different party sizes, information about the relative commonality of each size table, that there should be about three 2-tops for every two 4-tops:

$$x = 59/41 y; \text{ so that}$$

$$x = 1.44y$$

Those of you who remember high school math will recognize that we have two unknowns and two equations, which we can solve by substitution:

$$2(1.44y) + 4y = 50;$$

$$2.88y + 4y = 50;$$

$$6.88y = 50; \text{ so that}$$

$$y = 50/6.88 = 7.27 \text{ tables}$$

Since we can't have a fractional number of tables, we'd round the number of 4-tops to 7, meaning that 28 of our 50 seats were allocated to 4-tops. Once we've set the number of 4-tops, we can then use our total seat restriction to set the number of 2-tops:

$$2x + 4(7) = 50;$$

$$2x + 28 = 50;$$

$$2x = 22; \text{ and so}$$

$$x = 11$$

The correct answer, then, is 11 two-tops and 7 four-tops, eleven 2-tops and seven 4-tops. But that answer seems to move us back toward the problem we noticed in the first place: empty seats in larger-than- necessary tables. Actually, that shouldn't happen, since the 11-7 table mix would give us the best way of matching capacity to demand. It's only as we added even more large tables that we would start to see the empty-seat phenomenon. The extreme case—and I'm sure you can think of restaurants like this—is where all the tables would be 4-tops (a 0-12 mix in our example). If a restaurant has all large tables like that, it seems to me that no one has thought about using the restaurant's capacity effectively. You might argue that it's esthetics that drives the choice of all large tables; I would counter that designers are not necessarily focused on *operations* and consequently are probably costing the restaurant in terms of missed sales opportunities. In any event, a better way of approaching the capacity issue is to provide a designer with some information about the desired mix of tables, with the charge of making it esthetically pleasing.

Greater Complexity

Now, the issue of finding the right mix of tables for a restaurant is still not as simple as what I've presented so far. Additional considerations include demand information, differences across parties, table combinability, randomness of real restaurants, rules for selecting parties, and the effects of demand intensity. I'll discuss each in turn.

A common challenge in hospitality businesses is the nature of the information on customer demand that is available. You have information on the number of customers that you actually served. This is referred to as *constrained* demand, but the true, or *unconstrained*, demand includes customers you didn't serve, for whatever reason. Constrained demand refers to the fact that once the business is at full capacity, customers will be turned away, so the demand is constrained by available capacity. For your decision making, the ideal information point is unconstrained demand.¹ Consider the differences in the two types of demand information in the context of determining the best mix of tables in a restaurant. If you use unconstrained demand information, then you'll be attempting to determine the best mix of tables for the restaurant's true customer mix. If, instead, you're using constrained demand, all you'll be doing is finding the best mix of tables for the mix of customers *who were already being served*. These are potentially quite different. Unfortunately, the easy information to obtain is the constrained demand, since that's what's in your POS data. Capturing information on the unconstrained demand can require some imagination: making sure, for example, to track declined reservations, or the number of people who walk away from your restaurant when they're quoted an estimated wait time. Also, it would be important to track the number of people who put their names on the wait list but then leave before being seated. Even with this information, however, you still wouldn't have unconstrained demand information, because you wouldn't have information on customers who took one look at your restaurant and left because it appeared to be too busy. Again, employing some creativity would allow you to try to capture some of that information.

The example I presented earlier was limited to parties no larger than four people. But that's not entirely realistic because you'll always have larger parties. Also, certain characteristics of parties vary by party size. First, dining duration is typically longer for larger parties than for smaller parties. Second, larger parties tend to spend less per person than do smaller parties. Third, the space required to seat large parties can be different, on a per-person basis, than it is for smaller parties. All of these differences mean that the problem of finding the best table mix is more complex than the simple example presented earlier. Yet another consideration is whether tables can or should be combined to seat larger parties, or whether it's better to have a mix of different table sizes in the restaurant. Further, the differences across party sizes typically result in the large parties being worth less on a space-time basis than smaller parties. So, if you find that your unconstrained demand is sufficiently high, your restaurant might consider cherry-picking its more valuable, smaller parties and turning away business from the larger parties.

So, do you have any ideas on how to modify the "back-of-the-envelope"—type calculations (in Figure 10.1) to find the best mix of tables in a restaurant? ("Back-of-the-envelope" calculations can be done by hand or with a calculator.) Certainly, those equations could be modified to take into account differences in party characteristics. However, even with those modifications, the equations would leave out an important characteristic of real business: chance. The only way to deal with chance is to use a model that mimics the chance occurrences. In the restaurant setting, chance—or randomness—exists when parties arrive, the size of the party, the duration of the dining

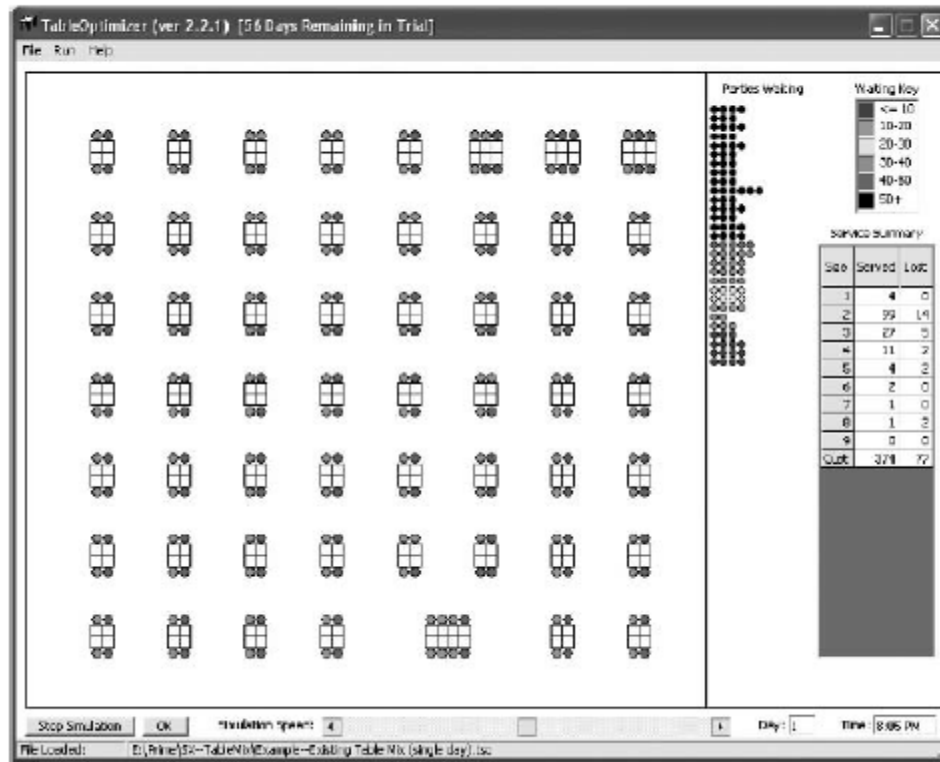
experience, how long customers are willing to wait for a table, and how much they spend. With a model that incorporates chance, we can examine such issues as the rules used to select a party to assign to a newly available table. Should the table be given to the party that's been waiting the longest (regardless of size)? The party that's been waiting the longest that has the "right size" for the table? The largest party that fits in the table (with ties broken by the longest wait)? Or a party selected in some other way? A model that incorporates chance would also allow us to evaluate the accuracy of the back-of-the-envelope calculations. (As an aside, a recent study I conducted found that the back-of-the-envelope calculations can yield table mixes that underperform the ideal mixes by more than 10 percent).

Simulation Models

Models that incorporate chance are called *simulation models*, since they simulate the kinds of things that can happen in the real world. The great advantage of using simulation models for operations is that they allow you to simulate different operations scenarios without having to change them in the real business. This means that your customers are not part of "an experiment" to see how to better serve them, with all the risks that entails. Using simulation, you can find those scenarios, configurations, or plans that improve on the status quo. Implementing those plans greatly increases the chance for successful changes to operations. Over the years, I've found simulation to be invaluable, since it allows me to create models that mimic the complexity that exists in real organizations. Simple simulation models can be constructed in spreadsheets such as Excel, though more complex spreadsheet models generally require the use of commercially available simulation software or custom-built software models. (For a more thorough coverage of simulation, see the article I wrote with Professor Rohit Verma entitled "Computer Simulation in Hospitality Teaching, Practice and Research," which is available free of charge from the Cornell Center for Hospitality Research at www.chr.cornell.edu.)

Figure 10.2 shows a screen capture of TableOptimizer, a restaurant simulation tool that I developed and frequently use in research projects. This screen capture was taken at 8:05 PM in the simulation of a real restaurant, and displays the status of the restaurant at that time. The restaurant in question had three 6-tops, while the other 53 tables were 4-tops. Green seats are occupied, while red seats are empty. The table of 8 seats in the bottom center represents two 4-tops combined to seat six people. There are 29 parties waiting for a table, 15 of which have been waiting for more than 50 minutes. To this point, 374 customers have been served, and 77 customers were "lost," having departed because their wait was too long. At the time shown, all of the tables were occupied, but only 122 of the 230 seats were occupied, yielding a 53-percent seat occupancy. In my studies, seat occupancies over 80 percent are achievable if the table mix matches well the customer mix. In fact, after changing its mix of tables, the restaurant in question was able to increase its effective capacity by approximately 30 percent.

Figure 10.2
Screen Shot of the TableOptimizer Restaurant Simulator



Example 2- Workforce Staffing

A challenge common to many hospitality businesses is dealing with the staffing challenges resulting from seasonal demand swings. If your operation is steeply seasonal, perhaps you staff up and staff down as the season changes, but it's worth asking the question of whether you might be better off if you held the staff size constant throughout the year. If you did that, you would have to determine what level would be best. If you do staff up and staff down, you need to determine an appropriate mix between permanent and seasonal staff. Then there's the issue of whether you should contract with outside vendors to supply some of the capacity needed during the peak season. In all of these decisions, the issue becomes how to best meet the demand.

To begin with, a plan to deal with seasonal demand swings should be high-level and deal with groups or types of employees for two reasons. First, the detail required to develop a plan specific to individual employees over an extended period would be impractical. Second, even if the detail could be managed, the random turnover of individual employees would soon make any plan out of date. As such, I'll use the term *employee category* to refer to a particular type of employee, such as full-time, seasonal, or contract.

In addition to the seasonal demand swings, other factors that compound the difficulty of making the staffing decisions are attrition rates, productivity rates, learning curves, labor costs, costs of hiring or terminating employees, and value gained from alternate task assignments—all according to employee categories. Each month, you face similar decisions: how many employees should be hired and how many should be terminated, by employee category. Clearly, these decisions are related, since the number of employees hired in one month affects the number of employees on staff in the next month, which in turn can affect the hiring decision in that month.

If a manager did not take a scientific approach to this problem, using a decision model, then the best he or she would be able to do is to use some rule of thumb that probably would mean being overstaffed at some times, being understaffed at other times, and not delivering the service as cost effectively as possible. Figure 10.3 shows one way that you might approach this problem scientifically. It does involve considerable calculation, but once the formulas are built, you can plug in your numbers.

Optimizing the plan presented in Figure 10.3 would involve finding the values of the decisions that yield the minimum total plan cost. That plan

Figure 10.3
Approaching the Workforce Staffing Problem Scientifically

Let's think about the parameters and decisions in the seasonal staffing context. Let's define:

e — index for employee categories;

m — index for months;

A_e — attrition rate of employees in employee category e , measured as a proportion;

D_m — aggregate level of customer demand that is forecast for month m ;

C^L — monthly labor cost of an employee in category e ;

C_e^L — cost of hiring an employee in category e ;

C_e^H — cost of terminating an employee in category e ;

P_e — monthly productivity an employee in category e ; and

S_{em} — number of employees on-staff in category e at the start of month m .

The decisions to be made are:

H_{em} — number of employees hired in category e at the start of month m ; and

T_{em} — number of employees terminated in category e at the end of month m .

There are two types of relationships between the decisions. First, the number of staff on-hand at the start of a month in an employee category is equal to the number of staff on hand at the start of the previous month, less the number lost through attrition in the previous month, less the number of employees terminated at the end of the previous month, plus the number of employees hired in the current month, or:

$$S_{em} = S_{e,m-1} \star (1 - A_e) - T_{e,m-1} + H_{em} \quad (\text{for each employee category } e \text{ and month } m).$$

The second relationship ensures that demand is met every month:

$$\sum P_e S_{em}^* (1 - A_e / 2) \geq D_m.$$

sum over employee categories

This relationship sums, across the employee categories, the productivity of the employees on-staff and ensures that it equals or exceeds the demand forecast. The staff on hand at the start of the month is adjusted downward, assuming that attrition occurs evenly over the month, so that the average number of staff available in a month is

$$S_{em}^* (1 - A_e / 2).$$

Finally, we have the expression that measures the overall cost of the plan (don't panic, it's not as bad as it looks!):

$$\text{Total Cost} = \sum_{\substack{\text{sum over} \\ \text{employee} \\ \text{categories}}} (\sum_{\substack{\text{sum} \\ \text{over months}}} C_e^L \star S_{em}^* (1 - A_e / 2) + C_e^H \star H_{em} + C_e^T \star T_{em})$$

In words, the cost of the staffing plan is the sum, across all employee categories and all months, of the labor costs, the hiring costs, and the termination costs. As with the demand relationship, we adjust the number of staff available at the start of a month S_{em} by $(1 - A_e / 2)$ to get the average number of people available in a month would show the ideal composition of the workforce and how its composition would change over time. For the optimization to be effective, the plan would have to have a planning horizon of at least one seasonal cycle (i.e., at least one year). Having a scope of less than a year would be problematic because the best plan for a partial year would almost always be different from the best plan for an entire cycle. If the complexity of the staffing model is modest, the plan could probably be created in Excel using its Solver capability (which is limited to 200 decisions). If the complexity increases, or if speed is an issue, commercially available optimization software could be used or a custom-built optimizer created.

This planning process would be ongoing—and you would repeat it every month. The reason for this is that both demand forecasts and the actual status of the workforce at the start of the plan will change. Clearly, there would be up-front effort involved to collect data to populate the model and to construct the model; that effort, however, would pay dividends through better staff planning. You would have the confidence to know that hiring and termination decisions are being made at the right times, for the right numbers of employees, of the right categories, to yield the best overall performance. Moreover, a plan like this would offer a reality check on organization's past decisions about labor staffing.

Once again, I have taken some liberties in presenting this example in a somewhat simplified manner. Ideally, the model would incorporate such other factors as the learning curve of employees and the value of alternative assignments (to be used when capacity exceeds demand). In addition, the plan lumps together all types of demand into something called “aggregate demand,” which assumes that all employees can do the work. It may be preferable to

separately plan different parts of the business.

As an example of a model for solving a problem like this, I refer you to the “Workforce Staffing Optimizer” tool that I developed, which is available free of charge from the Cornell Center for Hospitality Research. The tool, which uses a sophisticated, custom-build optimizer, allows for up to four categories of employees and a large number of inputs defining each employee category.

Paging Officer Data

To summarize my key points about managing operations scientifically, good data enable analysis, which then can support building and solving decision models. Let’s assume you have bought into these ideas, but you are wondering who would have the time to devote to managing operations scientifically, based on all these data requirements. You might also be concerned that you don’t have the time, skill, or interest to do all this analysis and model building yourself. Well, it doesn’t have to be you! You can find an appropriate employee or vendor and say, as Captain Picard was fond of saying, “Make it so.” Managing operations scientifically does require an up-front time commitment to data collection, analysis, and model building. You will see benefits in the form of better decisions, a more robust organization, greater profitability, and personal advancement. Your key role, then, is to be aware of the benefits and to know the extent of what is possible, so that you can either do the requisite work yourself or direct others to do it.

While this chapter has used two primary examples, many more examples can be found at the Cornell Center for Hospitality Research (www.chr.cornell.edu). Figure 10.4 lists some of the reports and tools available there, related to scientific management of operations.

Managing operations scientifically does not make managing a business “clinical.” Being a good operations manager is still as much art as science. The point is, though, by focusing on the science part of it, you’ll be more valuable than ever to your organization.

Figure 10.4
Reports and Tools Available from the
Cornell Center of Hospitality Research That Offer Examples
of Managing Hospitality Operations Scientifically

-
- Cases in Innovative Practices in Hospitality and Related Services: Set 3, 2010, *Cornell Center for Hospitality Research Report*, Vol. 10, No. 10 (Cathy A. Enz, Rohit Verma, Kate Walsh, Sheryl E. Kimes, and Judy Siguaw).
- Integrating Self-Service Kiosks in a Customer-service System, 2010, *Cornell Center for Hospitality Research Report*, Vol. 10, No. 6 (Tsz-Wai Lui and Gabriele Piccoli).
- Cases in Innovative Practices in Hospitality and Related Services: Set 2, 2010, *Cornell Center for Hospitality Research Report*, Vol. 10, No. 4 (Sheryl E. Kimes, Cathy A. Enz, Judy Siguaw, Rohit Verma, and Kate Walsh).
- The Eight-Step Approach to Controlling Food Costs, 2009, *Cornell Center for Hospitality Research Tool* (J. Bruce Tracey).
- Revenue Management Forecasting Aggregation Analysis Tool, 2009, *Cornell Center for Hospitality Research Tool* (Gary M. Thompson).
- Cases in Innovative Practices in Hospitality and Related Services: Set 1, 2009, *Cornell Center for Hospitality Research Report*, Vol. 9, No. 17 (Judy Siguaw, Cathy A. Enz, Sheryl E. Kimes, Rohit Verma, and Kate Walsh).
- How Restaurant Customers View Online Reservations, 2009, *Cornell Center for Hospitality Research Report*, Vol. 9, No. 5 (Sheryl E. Kimes).
- Don't Sit So Close to Me: Restaurant Table Characteristics and Guest Satisfaction, 2009, *Cornell Center for Hospitality Research Report*, Vol. 9, No. 2 (Stephani K. A. Robson and Sheryl E. Kimes).
- The Wine Cellar Management Tool, 2008, *Cornell Center for Hospitality Research Tool* (Gary M. Thompson).
- Service Scripting: A Customer's Perspective of Quality and Performance, 2008, *Cornell Center for Hospitality Research Report*, Vol. 8, No. 20 (Liana Victorino, Rohit Verma, and Don Wardell).
- Forecasting Covers in Hotel Food and Beverage Outlets, 2008, *Cornell Center for Hospitality Research Report*, Vol. 8, No. 16 (Gary M. Thompson and Erica D. Killam).
- Accurately Estimating Time-Based Restaurant Revenues Using Revenue per Available Seat- Hour, 2008, *Cornell Center for Hospitality Research Report*, Vol. 8, No. 9 (Gary M. Thompson and Heeju Sohn).
- Complaint Communication: How Complaint Severity and Service Recovery Influence Guests' Preferences and Attitudes, 2008, *Cornell Center for Hospitality Research Report*, Vol. 8, No. 7 (Alex M. Susskind).
- Workforce Staffing Optimizer, 2007, *Cornell Center for Hospitality Research Tool* (Gary M. Thompson).
- Customer Satisfaction with Seating Policies in Casual-Dining Restaurants, 2007, *Cornell Center for Hospitality Research Report*, Vol. 7, No. 16 (Sheryl E. Kimes and Jochen Wirtz).
- Examining the Effects of Full-Spectrum Lighting in a Restaurant, 2007, *Cornell Center for Hospitality Research Report*, Vol. 7, No. 12 (Stephani K. A. Robson and Sheryl E. Kimes).
- The Effects of Organizational Standards and Support Functions on Guest Service and Guest Satisfaction in Restaurants, 2007, *Cornell Center for Hospitality Research Report*, Vol. 7, No. 8 (Alex M. Susskind, Michele K. Kacmar, and Carl P. Borchgrevink).
- Restaurant Capacity Effectiveness: Leaving Money on the Tables, 2007, *Cornell Center for Hospitality Research Report*, Vol. 7, No. 7 (Gary M. Thompson).
- A New Method for Measuring Housekeeping Performance Consistency, 2006, *Cornell Center for Hospitality Research Report*, Vol. 6, No. 11 (Michael C. Sturman).
-

- Dining Duration and Customer Satisfaction, 2005, *Cornell Center for Hospitality Research Report*, Vol. 5, No. 9 (Sheryl E. Kimes and Breffni Noone).
- Perceived Fairness of Restaurant Waitlist-Management Policies, 2005, *Cornell Center for Hospitality Research Report*, Vol. 5, No. 4 (Kelly A. McGuire and Sheryl E. Kimes).
- Restaurant Table-Mix Optimizer, 2004, *Cornell Center for Hospitality Research Tool* (Gary M. Thompson).
- Workforce Scheduling: A Guide for the Hospitality Industry, 2004, *Cornell Center for Hospitality Research Report*, Vol. 4, No. 6 (Gary M. Thompson).
- Hotel Managers' Perceptions of the Blackout of '03, 2004, *Cornell Center for Hospitality Research Report*, Vol. 4, No. 4 (Robert J. Kwortnik).
- Restaurant Revenue Management, 2004, *Cornell Center for Hospitality Research Report*, Vol. 4, No. 2 (Sheryl E. Kimes).
- Emergency Preparedness Essentials, 2003, *Cornell Center for Hospitality Research Tool* (Robert J. Kwortnik).
- Key Issues of Concern for Food-service Managers, 2003, *Cornell Center for Hospitality Research Report*, Vol. 3, No. 4 (Cathy A. Enz).
- Dedicated or Combinable? A Simulation to Determine Optimal Restaurant Table Configuration, 2003, *Cornell Center for Hospitality Research Report*, Vol. 3, No. 2 (Gary M. Thompson).
- Multi-Unit Restaurant-Productivity Assessment: A Test of Data-Envelopment Analysis, 2002, *Cornell Center for Hospitality Research Report*, Vol. 2, No. 1 (Gary M. Thompson and Dennis Reynolds).
-

NOTE

1. E. B. Orkin, "Wishful Thinking and Rocket Science: The Essential Matter of Calculating Unconstrained Demand for Revenue Management," *Cornell Hotel and Restaurant Administration Quarterly* 39(4) (August 1998): 15 — 19.