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## Performance Modeling of Service Businesses

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*Abstract*

Business performance continues to be one of the principal subjects in enterprise operations. The evolution of the service economy brings renewed interest to the field of performance modeling. Senior managerial decision makers constantly seek to improve the performance of an organization. Key areas of interest are what aspects of the business are important for successful performance, and how best to control them, e.g., what investments, resource allocations, and other actions must they take to maximize business performance. Our ultimate goal is to develop quantitative models and associated methods or tools that will help high-level managers of services businesses improve their performance. We believe that most organizations could improve their understanding of what drives their performance by following a more rigorous methodology. In this paper, we explore the possibility of modeling performance through learning from a number of diverse technical areas and insights from decision makers of an existing service business.

***Index Terms* — service science, performance analysis, business performance modeling, enterprise management**

## I. Introduction

CONSIDER a commercial enterprise whose primary business is to provide a certain set of services to their customers. A primary job of the chief executive of such an enterprise is to increase its shareholders' value by improving its business performance. An immediate question is what we can do to improve the performance: should we hire more people, enter new markets, consolidate operations, etc? Many of these relatively obvious options may improve certain aspects of performance, but may degrade others. There may also be many other options that are not apparent. So to answer the question effectively, one needs to identify the important factors that impact business performance and analyze carefully the effect of changing one or more of the controllable factors. A decision can then be made on what actions to take, considering the tradeoffs among the many possible controls and their implementation issues.

In this study, we explore the possibility of developing a quantitative model to help the chief executive improve the performance of his/her enterprise. Utilizing the model, the chief executive will be able to estimate the effects of possible decisions or strategies (defined by a set of decisions) before they are implemented. Such what-if analyses will lead to more effective decisions on how business performance can be improved with a given level of resources. At the same time, more robust decisions

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can be made to minimize the risk. For example, decisions can be chosen such that even worst cases will yield acceptable results. The model can also be used to plan for actions to respond to changes in the environment. For example, if labor costs increase rapidly, what will happen to the business performance? What can be done to mitigate the effect?

Such a quantitative model is different from a typical predictive model (such as a predictive data mining model) in nature, although some of the methodologies developed there may be applicable in some steps of developing a performance model. Because a primary purpose of our model is to estimate the effect of an action the enterprise takes, we need to build causal relationships into the model. A causal relationship could be an empirically established relationship through experiments or observations, or a mechanistic relationship through the execution of a sequence of known operations. The latter kind of relationship is ideal, since we actually understand how a cause gives rise to an effect. In business performance models, it is often not possible to find such a relationship. For example, since businesses serve human beings and so most performance models will involve some level of human behavior which cannot be modeled as mechanistic relationships at present or in the foreseeable future.

A predictive model could also be a causal model, but not necessarily so. It is often easier (but still far from trivial in most cases) to capture correlational relationships since we do not need to understand the exact, underlying causal phenomenon, so predictive models tend to be correlational models. This is particularly true if the model is found by automatic mining or data analysis algorithms applied in a large database of empirical data. While such a model is very useful for prediction (e.g., prediction by using leading indicators), it may not be helpful in determining actions. For example, while it may well be true that the sales of beers is correlated with the sales of diapers, one may not want to boost beer sales by promoting diapers. Table 1.1 shows a comparison of predictive models and causal models.

Our research goals can be summarized as follows. The first goal is to model business performance. Businesses can be viewed and decomposed in many ways (processes, components, resources, etc.) How do we create a `performance view' of a business, enabling decision makers to optimize business performance? What business elements should be modeled? How do we determine their relationships? For example, how do we establish a causal link between "investment in knowledge management" and "revenue growth", if one exists? How do we determine the optimal configuration of the key decision variables or at least the interventions that could improve the system?

The second, related, goal, is predictive capabilities. What are the best leading indicators ("key performance indicators" or KPIs) that predict how the business will play out over time? What are the best indicators of the "health" of a business? What governs the evolution of main industries? For example, how will deconstruction (e.g., IT outsourcing) affect growth?

In this paper, we discuss the first few steps we have taken to develop such a performance model. There are several key study design issues that need to be resolved before any model can be built; these are discussed in Section II. We have made an attempt to learn from several different fields of study and practice, each of which provides significant insight into some facet of business performance. Section III reviews very briefly the state of the art in these fields and their relevance to our subject. We hope to combine our learning from the diverse literature with knowledge to be elicited from the decision makers themselves: executives who must manage their business with or without the help of modeling. Section IV describes our proposed approach to developing a performance model for analysis at the level of interest of the chief executive. A conceptual design of the performance model is explained in Section V, using a simple example. We offer some concluding remarks in Section VI.

Table 1.1. Comparison of Predictive Models and Causal Models

| | **Predictive Models** | **Causal Models** |
|---|---|---|
| **General purpose** | Predict an outcome so that tactical actions can be taken to increase the chance of seeing a favorable outcome | Discover causal relationships to help understand the underlying structure of a phenomenon |
| **Example of business purposes for a service business** | To help discover customers that are most likely to buy selected services, so that sales effort can be targeted towards them for more effective use of sales resources | To help understand what factors are most influential in a successful sale of selected services, so that resources can be directed towards the identified factors for more effective use of investment |
| **Application example in a service business** | What customers should we go to next to sell selected services? | What can we do to sell more selected services to our customers? |
| **Methodology for development** | Data mining methods, e.g. regression trees, associations; statistical methods, e.g. various regression methods | Design of experiments, causal modeling methods |
| **Typical factors** | Observable quantities | Observable and unobservable quantities |
| **Focus** | Tactical focus to identify an observable pattern within a confined area. Application of the pattern is within the same area, so that pattern identification without a clear understanding of the underlying reasons is adequate. (This does not preclude the fact that most data mining results have to pass a reasonableness test, i.e. the user usually requires some reasonable explanations of the results. This is done outside of the model and is not the same as discovering the relationships between the reasons and the quantity of interest.) | Strategic focus to understand the underlying reasons, such that a desirable pattern observed in one area can be replicated in other areas. A more in-depth understanding of the underlying structure is needed. |
| **Cross usage** | Can be used as a starting point for a causal model, since some of the factors used for prediction may actually be causal in nature. | Can be used for prediction also, but the input data required may take more effort or be more difficult to obtain |

## II. Key Issues in Business Performance Modeling

### A. *What Is Successful Performance?*

There are many measures used to loosely represent the notion of business performance, including revenue, profit, earnings per share, return on assets, return on sales, market value of the firm, asset turnover, operating income to assets, and so on. There is no single measure that is universally accepted [20], since no single measure can capture all aspects of business performance.

In studies on the value of information technology to a business, return-on-assets and return-on-sales are perhaps most widely used as the performance measures. This is a logical choice from an investment point of view. If one takes the view that the ultimate goal of a business to make a profit for the owners who invested capital in buying assets for the company, return-on-assets will be one of the most important measures. For this reason a large fraction of recent papers we have reviewed includes return-on-assets as one of their performance measures. By comparing the return-on-assets of a business with the nominal return of alternative assets the owner could have invested in (such as government bonds), we can determine the economic value added of the business.

In many ways economic value added can be considered an ultimate measure of performance. However, similar to many other measures calculated using historical data, it only looks at the past. In contrast, market capitalization looks at the future, at least theoretically. In addition, it includes intangibles and other non-financial advantages of a business. Indeed Gerstner [15] considers it the ultimate measure of success.

Another critical measure to consider is revenue. Revenue is typically a good indicator of the level of resources (e.g., number of people, manufacturing capacity) needed for the business to run at their operational level. This is perhaps even more so in service businesses where the work is heavily performed by humans. As such, revenue is used as a normalization factor for many other performance measures, such as profit (e.g., return on sales, gross margin). Calculating these normalized measures requires revenue, so a model for revenue would be useful in many places.

One of the most widely used measures of a publicly traded commercial enterprise is earnings per share (EPS). Although not without flaws, its significant influence on the stock price (e.g., [26]) and its capability to allow performance comparison of the same enterprise across time and, to a lesser extent, performance comparison across enterprises make it one of the top concerns of senior management.

Since EPS involves two control variables, profit and number of outstanding common shares, EPS can be unduly influenced by factors that are not representative of good performance. For example, stock buy-backs decrease the number of common shares hence increasing EPS. However, the cash used to fund buy-backs will decrease the amount for alternative investments (such as acquisitions or internal research and development), potentially decreasing profit at some future time. As a result, the decision to buy back shares is a complex one that requires an entire level of analysis and optimization.

Keeping it simple, we prefer to focus instead on earnings or profit, in place of earnings per share, for our research. Earnings will also be used in calculating many other important financial measures, such as return on assets, return on shareholder equity, and of course EPS.

One of the difficulties in studying performance is that time plays a significant role. For example, the Ford Motor company was considered one of America's leading firms but is now not so successful by all accounts. Most would agree that successful performance should be measured not just as a transitory concept but as something that is sustained over a reasonable time horizon. Some would argue that survival is itself the measure of success. However there is no standard time span for measuring success or survival; in practice, most management science researchers appear to focus on a decade.

Time appears in another form as well: rate of change in each of the performance measures discussed above. For example, most business executives will consider revenue growth (i.e., change of revenue year to year) alongside revenue to be measures of success.

The notion of growth can be further analyzed. Executives desire `organic growth' and `balanced growth'. The former refers to an increase in revenue that arises fundamentally due to ongoing operations, and not due to other reasons such as mergers and acquisitions or unusual financial investments. Balanced growth describes a situation in which profit growth keeps pace with revenue growth. Increasing revenues with decreasing profit margins are considered a disconcerting sign of poor performance. These again reflect the need to use more than one measure in judging performance.

At this time, we have chosen to initially focus our research around three primary measures of performance: annual revenue, revenue growth, and profit. All are understood to be functions of time, and the interest is in building models that are robust and accurate at least within a 5 to 10 year horizon. We expect that models for other commonly used measures such as return on sales and earnings-per-share could be built using models for the above measures.

## B. *What Drives Successful Performance?*

Assuming we have agreed upon a measure of performance, the next question is what influences that outcome?

Reference [20] provides a good review of the major studies that have attempted to uncover the drivers of firm performance. Hammer [17] writes that designing and using metrics to track and improve operating performance is one of the most persistent problems organizations face. To help select the right metrics, he proposes (among other things) to focus on end-to-end business processes that create value for the customer. In general, there is long-standing uncertainty and debate as to what metrics truly drive enterprise results.

A complication is that there are a number of intangible factors believed to impact enterprise performance. For example, Bloom et al. [7] find that the quality of management has a deeper effect on performance than the country, the regulatory environment, or the industry sector where a company operates. While the 700 companies sampled are from the manufacturing sector, the study concludes that there is a strong link between how well managers adopt best practices and how well a company performs.

Even factors that are tangible, such as those related to resource levels (e.g., financial budget or physical production capacity) may not be straightforward to deal with. One issue is that there are usually other factors that impact the effectiveness of that driver. For example, physical production capacity will be affected by how well the production schedule utilizes the capacity and the production yield. It may therefore be more convenient to use "effective production capacity" as an intermediate or latent variable, which in turn is modeled by a function of physical production capacity and yield, quantities that are directly measurable.

It can be argued that services businesses are more difficult to measure and monitor than manufacturing processes, primarily due to higher variances in services than in manufacturing. For example, the skill levels applied could be quite different even in the delivery of the same service, or customer behavior or requests could be erratic, and as a consequence unplanned sources of cost are driven into the service. Such variances compound the analytical challenge.

Finally, an underlying problem is that of measuring performance data with accuracy. Data are rarely defined and collected in a consistent way through different units of the same company. In addition, many metrics are chosen based on finance considerations alone. Services businesses are particular vulnerable to this type of data collection problem, particularly with respect to measuring variable costs and in particular, the most important source of it, i.e., people. The limited availability of data can severely constrain the choice of performance drivers studied in a model

To illustrate the difficulty in discovering drivers of performance, we note an early study by Peters and Waterman [28] which claims that managerial actions and attitudes are the critical success factors. The study was quite unscientific, with a notably odd sampling process. Several decades later, it seems clear that the study failed to uncover the true drivers of performance, since many of its "successful" companies have subsequently performed poorly or ceased to exist.

## C. *Methodological Issues*

After the performance measures (dependent variables) and their drivers (independent variables) are chosen, we can start developing a model linking the performance measures and the drivers. There are many issues in this step, which are more of a technical nature and are outside the scope of this paper. One of the most important issues in model fitting is the ability to detect the presence of confounding of effects of different drivers. An observed correlational link between factors $X_1$ and Y may not reflect a cause-and-effect relationship, but rather is due to a third factor $X_2$ that affects both $X_1$ and Y. If $X_2$ has been omitted from the study, it will result in a biased estimate of the effect of $X_1$ on Y. By this nature, observational studies that consider and model a narrow set of explanatory variables are likely to suffer from such bias due to the effects of omitted variables. In the subject of studying the impact of IT on firm performance, Tippins and Sohi [37] argue and investigate the possibility of organizational learning as a missing factor that confounds the effect of IT on performance.

Because it is impractical to include a huge number of dependent variables in an empirical study, there is a need to be able to detect the possibility of missing factors that might have confounded the main effects estimated. Although many new techniques in causal modeling and the design of observational studies (e.g., [27], [32]) have been developed in the recent two decades, this issue of detecting confounding effects remains open. At present, one of best strategies to minimize this issue is to consider a comprehensive list of factors that will either account for most possible effects or will block other factors that are not considered. Employing the concept of blocking (see, e.g., Chapter 1 in Pearl [27]) is especially useful, since only the most immediate or direct factors need to be identified, as opposed to all possible factors that influence our dependent variable. Nevertheless, identifying immediate factors is very much an art at this time.

A performance model will likely involve factors that are subjective in nature or are latent variables that can only be captured (partially) by some subjective measures. All issues relevant to organization studies, such as access to subjects and bias in responses, apply. Bryman [10] contains a comprehensive discussion of issues specific to organization studies using common methods such as surveys or case studies. Even though social studies might use the same or similar research methods, organization studies tend to have their own distinct set of issues.

A common issue in organizational behavior studies is the unit of analysis (e.g., as discussed in Bryman [10]): should the study be done at the level of the individual, a group or department, a business unit, or the firm? As we are interested in the performance of an enterprise, our unit of analysis is naturally the firm level. This brings at least two issues. First, many enterprises engage in several different types of businesses and each type will have its own performance characteristics. Conglomerates are an extreme example. Each type of business most likely will require its own performance model involving different factors, or even different model development methodologies. This dictates a model at the business unit level. In addition, because usually there is a good reason for the enterprise to pursue different businesses (e.g., economy of scope), these business-unit level models may interact. Developing multiple, possibly dependent models adds tremendous difficulties to the already hard task of developing a single model. Second, a firm level model would likely require data about competing firms which are generally not available to outsiders. A firm wanting to build its own performance model is thus hindered by the lack of data on its competitors. This is probably true for most organization studies at the firm level. It is no surprise that most quantitative models in use by a business today rely mostly on data available within the firm (e.g., demand forecasting models, supply chain planning models).

## III. RELATED RESEARCH

We briefly review a number of different technical areas that are relevant to our study. Many of these are entire research topics with a substantial literature. We touch on the key issues that pertain to our objective and potential applications to our subject of interest.

### *A. Performance models in organizational behavior and management science*

The academic literature has studied many facets of businesses, especially from the economic, anthropological, managerial, and operations perspectives. We found that the literature on organizational behavior most directly addresses the subject of enterprise-level business performance. Recent papers in the field include [2], [3], [5], [13], [14], [22], [29], [30], [33], [34], [36], [39]. The papers in this field typically select a measure of performance such as revenue or return-on-assets as the dependent variable, and attempt to explain differences between firms using a handful of factors of interest in each study. These studies vary widely in their choice of explanatory variables, e.g., customer loyalty, innovativeness of the firm, quality of management, speed of decision making, investment in IT, corporate culture, etc. We have not found a comprehensive study that simultaneously studies a wide range of factors and explains their relative influence on performance.

Most of the published studies follow a common approach:

1. They guess what aspects of a firm might have impact on its performance, usually choosing one of the common financial measures such as annual revenue or profit as the measure of performance. Then they review the prior literature on these aspects and formulate explanatory variables and hypotheses.
2. They collect data, through survey questionnaires mostly. A few studies use published or existing data.
3. They fit a model using a variety of techniques such as structural equation modeling or forms of regression.
4. Then they show statistical evidence from the fitted model to support their hypothesis.

While these models give some leads on what independent variables might be of interest and are useful to derive some high level insights, they are not suitable as an aid for decision making. This is because:

1. The independent variables are too high level and are not directly controllable by a decision maker.
2. The hypotheses (and hence the model structure) are simplistic. Most results are highly intuitive and often the model results do not add any substantial insight to the intuition of senior executives.
3. Often the model fit is poor, making the model coefficients unreliable. One cannot draw any reliable conclusion beyond directional or relative magnitudes.
4. The studies are oriented towards a single or a few related issues or factors influencing business performance. In other words, the objective is to distinguish whether the factor of interest has a significant effect and conclusions can be drawn as soon as the effect is seen, controlling for a minimum number of factors that might mediate the main effect. Such a nature is inconsistent with a business performance model where we want to identify as many factors as possible that are relevant and practical. Further, the varied choice of dependent variables, methodologies, and model structures across studies not only makes it hard to compare the findings of any two studies, it also makes it difficult to develop a unified perspective that combines the learning from multiple studies.

Reference [23] provides a great review of the difficulties involved in creating scientific theories of organizational performance. They identify the central problem as that of understanding the true causal structure of organizational performance phenomena, and describe several difficulties in building theories that explain performance. The most notable of these difficulties are (a) Diffusion of information about the apparent determinants of performance through all the organizations studied, and subsequent elimination of variation between the organizations, making it difficult to study those variables. (b) Oversimplified theories, e.g., omitting feedback loops which are likely to be critical. (c) Data are usually obtained via retrospective recall, which enables respondents to reconstruct the past in a way that is consistent with subsequent performance results and conventional beliefs. The authors observe that the organizational research community admits that causal inferences about performance are often unjustified but nevertheless goes on to make those inferences.

Nevertheless, we learn valuable lessons from studies in this area, particularly the factors that have been identified and the research methodologies used. Many of the issues faced in these studies, such as those in data collection and model fitting, will be similar to what we are going to embark on.

### *B. Key performance indicators and benchmarks*

Key Performance Indicators (KPIs) have become a common language among practitioners. While many issues remain, KPIs have reached unprecedented levels of standardization, as demonstrated by efforts of a number of industry organizations, such as APQC and Supply Chain Council. While these two have published the most common cross-industry indicators, individual industries and their segments have also made significant progress toward defining the KPIs that capture the business concerns in their specific operations. Industry-specific data on these KPIs have been collected by APQC and others so that companies can benchmark their performance against sibling members of their industry.

These activities imply that there is some common understanding on what indicators should be used in order to measure the performance of the main operations of a company. However, there has been no attempt to explain how the indicators relate to each other and how they collectively or individually impact the overall financial performance of an entire enterprise. For example, although many KPIs related to customer satisfaction have been identified, there is still no formal way to assess the impact of a one-point improvement in a customer satisfaction measure on revenue growth.

This area is important to us in the following ways:

1. The KPIs are excellent candidates for consideration as dependent or independent variables in our performance model. Many of these KPIs represent the collective experience of many executives in the industry. They are an invaluable source of information for our model development effort.
2. The industry-wide data set collected over time for benchmarking purposes represents an important source of historical data for model fitting.

### *C. Business performance management*

Over the years a number of significant developments have appeared in the subject of business performance management, one of which is the Balanced Scorecard (BSC) (see, e.g., [18], [19] and many others). It is remarkable to observe the enormous simplifications and levels of manual construction that are used in order to produce a BSC. The gaps this technique leaves up to the practitioner to bridge are so significant that almost no rigor is finally enforced. In fact, the original paper on BSC [18] presents BSC as a technique to map out business strategy, i.e., BSC is a tool to represent the four main dimensions of a business (learning, internal processes, customers and financials) and their connections in a visual form. This explains why so many people use the term "Balanced Scorecard" for different performance projects that may actually have very little in common or offer dubious chances of being repeatable from one company to another.

Most of the original ideas in Balanced Scorecards have made it to the academic literature under the form of a 'toolkit' for mapping out strategic initiatives and communicating them to affected company stakeholders. In fact, a number of research papers in this area that have followed the seminal Balanced Scorecard work have been criticisms or clarifications of the basic modeling proposition.

Another significant development is the introduction of the so-called "value drivers" connected in some intuitive way in an attempt to link metrics in a supposedly cause-effect model. Thus, 'trees' of value drivers have become commonplace to denote a business objective supported by a series of factors that drive the desired value. In many business consulting practices observed in the field, the arrows connecting these drivers are not explained except for reasons of practical experience or pure belief. Additionally, the independence relationships implied by these structures are rarely defensible; when used directly for quantitative analysis these models may produce biased or incorrect inferences about causal effect. Further, value driver trees built in this area are usually linear and fail to account for feedback loops and other more complex inter-linkages between the variables. However, the overall idea is indeed consistent with the philosophy of BSC which states that the measurements have to assess quantities that matter – those that have some significant influence on our business objectives.

The underlying approach of our business performance model is also similar in nature. We start with the ultimate measurement which will be predominantly linked to our business objective. For example, if our objective is to grow the revenue, then obviously revenue is one of the ultimate performance measures. Then, similar to BSC or value driver trees, we model this measure by a set of factors, many of which can be interpreted as performance measures. For example, revenue may be modeled as a function of service quality (among others) and service quality is a performance measure by itself.

Recently Spitzer [35] discusses performance measurement in the context of human and organizational behavior. A performance model can be used to help execute his proposed action plans, particularly in choosing what are to be measured.

### D. *Performance models of supply chains, manufacturing systems, and inventory systems*

Performance models of operational systems such as manufacturing systems, inventory systems, and supply chains are widely studied in the literature. Because these systems are completely man-made, the underlying phenomena are understood and, at least theoretically, can be modeled. Most of these models are therefore based on the capturing of the details of the operations in mathematical form. Both analytical models and computer simulation models have been used. Computer simulation models can be highly detailed but suffer in computational time. Analytical models are relatively simple approximations, in the sense that operation details represented in the model do not coincide with those in reality. However, they are sufficiently accurate for planning and obtaining insights. High level models, based on empirically fitting mathematical functions to represent performance over a range of parameter values, are used primarily to save computational effort, rather than as a means of understanding (unlike typical studies in the organizational behavior literature which has no other alternatives).

Manufacturing systems for discrete products are modeled using techniques of Markov Chains and queuing theory. Chapter 5 in [16] provides a brief overview of the field, while [11] contains a comprehensive treatment. Manufacturing systems for continuous, fluid-like products are modeled using combinations of differential and difference equations. It turns out that such fluid models are sometimes appropriate approximations for discrete manufacturing systems.

Inventory systems, ranging from single location systems (such as a standalone warehouse) to multi-level systems (such as a tier of warehouses serving another tier in turn serving the end customers), are extensively studied. The topic of paramount interest is to derive an optimal control policy so that the total system cost is minimized while satisfying certain service level requirements. Chapters 1-4 in [16] provide an overview of the vast literature. Pure performance models to predict the system performance (e.g., the average inventory level) given a set of control parameter values are actually less common. A possible reason is that solving a performance model is often as hard as calculating an optimal policy. Reference [31] provides a set of performance models for a class of single location inventory systems under fairly general conditions, based on renewal theory.

Supply chains are typically a set of manufacturing and inventory systems connected in some way, and with certain peculiar features. Due to the complexity of the entire system, computer simulation modeling is often used. Chapter 2 in [1] discusses the use of simulation models in supply chain planning and analysis. Reference [25] describes an example of using simulation in analyzing supply chains. Hybrid analytical and simulation models have also been used (e.g., [4]). Completely analytical models are relatively scarce; an early one is described in [12].

Performance models of supply chains, manufacturing and inventory systems are highly relevant to our performance model. Operations are often a major aspect of a service enterprise, contributing significantly to many enterprise level performance measures. Continuing with the above example of revenue as a function of service quality, service quality may in turn be a function of customer order lead times which are commonly found in supply chain models. We expect that a portion of our performance model is a supply chain or production model (though in our case production refers to production of services). In particular, the approach of using an empirically fitted model to approximate a detailed computation model such as simulation is attractive in our context, because our model will likely be quite large and computational effort may become a concern.

### *E. Optimization models*

Optimization models have long been used in industry. Applications range from engineering design (e.g., layout of electronic circuit boards), manufacturing (e.g., production planning and process control), quality control (e.g., inspection sampling) and distribution (e.g., warehouse location and truck routing). In the recent twenty years, optimization has been applied to the demand side of a business, such as optimal pricing in airlines and retail.

There is, however, very little literature on optimization modeling at the enterprise level, i.e., at the profit & loss statement level. The only paper we are aware of is an optimization model for the manager of a Soviet enterprise which is subject to central planning [38]. The manager of the enterprise is rewarded based on profit, production, and variance from a given target. A (deterministic) optimization model was developed to mimic this reward structure. Interesting properties of the optimal solution were derived to obtain insights on the behavior of the enterprise.

Our performance model will represent one step in the direction of developing enterprise level optimization models. For example, a model of revenue as a function of many controllable factors such as level of investment in employee skills or computing facilities will be a basis for an optimization model to determine the optimal allocation of available investment resources. In this simple example, the revenue model can directly be used as the objective function and other business constraints can be added to form a proper optimization model.

### *F. Marketing science models*

Similar to manufacturing system models, marketing science models provide mathematical studies on how to best manage resources, in this case, dedicated to marketing activities. One can also classify the models into performance models and optimization models. Performance models include empirical models of consumer behavior, effect of marketing, advertising, or promotion spending on business performance such as revenue, effect of pricing on demand, etc. Since the impact of marketing is on human behavior, empirical model fitting on carefully collected data is the key modeling strategy (unlike manufacturing system models). In this way they are similar to business performance models. For example, Chapter 7 in [6] develops a regression model to predict the effect of sales promotions on sales and market share.

Optimization models in marketing science calculate optimal ways to utilize marketing resources in order to maximize revenue or profit. Typically, one or more parts of an optimization model are performance models. For example, to maximize the revenue by varying pricing actions requires understanding the effect of price on revenue. See the many examples discussed in Chapter 4 in [1]. An excellent overview of marketing science models in general is in [21].

Performance models in marketing science will be very useful to us. Continuing again with the example of the revenue model, revenue can be modeled as a function of offering price relative to competition (among other factors such as service quality mentioned above). Price-demand models are a main research topic in marketing science. Although existing marketing science models may not be directly applicable to our performance model, their development approach and model structure will be useful in parts of the performance model, particular those that relate to demand.

## IV. AN APPROACH TO BUILDING PERFORMANCE MODELS

We now propose an approach to building robust business performance models. We plan to use IBM's service business as a pilot case and hope to build a model that will provide insight into its business performance. Modeling results based on real data will be reported in a future paper.

1. Identify the variables that will be captured in the model. We have identified Revenue, Revenue Growth, and Profit as the outcome variables of interest. We work backwards from these variables and ask what factors directly influence the outcomes; then in turn what influences those intermediate variables, and so on. In some cases the causal mechanisms identified may be purely deterministic (e.g., profit equals revenue minus cost), whereas in other cases the mechanisms are stochastic (e.g., revenue as a function of demand).

To provide solid empirical grounding for our choice of variables, we identify two important sources of input, in addition to the usual academic literature:

(a) The best practical source is the ethnographic interviews we have conducted with executives in the service practice. These executives span multiple domains such as marketing, strategy, and operations. They are often the best experts on the causal mechanisms at play, since they deal with the business daily. While an interview-based elicitation process has its own limitations, constraints on access to these busy people make it the most practical approach. Artifacts used by these practitioners, such as strategy documents, are valuable sources.

In order to better understand the needs of executives, we interviewed a number of high-level managers. These ranged from those in central headquarters, such as an Asset Controller for Budgets and Strategy in the CFO office, the Director of Opportunity analysis in Marketing, the VP of Human Resources for executive competencies, and the VP of Corporate Strategy, as well as those in Headquarters Economics areas involved in forecasting economic growth and modeling. In addition, we talked with those involved with consulting and partnerships with enterprise customers who regularly observed CEO decision making. For all we used a questionnaire which asked about the problems they've encountered in the recent past, as well as the problems they're currently facing. We inquired what executives at IBM and similar firms need to know more about concerning how their business works. What are the critical needs where we can help them?

We learned a number of surprising and useful pieces of information. Even those involved with the company business model said they do not fully understand what drives growth, and that a model which did would be providing great help. In particular, it was voiced that what we need was a model of the IT industry, and none exists today. Of course, current models make a stab at it, but such models are very unsatisfactory in several areas, particularly for IT services. Models should address questions such as whether the product mix is correct, and the timing of innovation. Another complaint was the lack of capability to input assumptions (such as major vendor software releases, economic conditions or global political events) and figure out what will happen to a company's demand for products and services. Still other desired variables involved the effect of outsourcing geographies, and answering questions about where a company should invest next.

Key requests were models which could link control variables to performance measures such as earnings per share. Questions to answer include what the indicators are that explain companies' or business's health. What are the things we need to bear in mind in cycles longer than what the indicators measure? What are the best measures of persistency and resilience? If a manager is going to make changes and investments, show how this is going to affect that area's performance, how much income the changes will make.

Our interviews also taught us a great deal about how the company officially does strategy, and help explain how our models can fit into that process. In addition, such models would be of use to the consulting business, and executive dashboards with the true ability to drill down are the real goals.

(b) The second source of input is variables from other models that are in actual use today. For example, macro-economics models for the U.S. (e.g., [9]), benchmarking and other publicly available databases such as Hoovers or Dun & Bradstreet may provide a number of relevant variables.

2. Obtain quantitative data on the variables identified above and analyze them using mathematical techniques. We are currently exploring a 'bottom-up' approach starting with the exploration of readily available data sources (e.g., data that have been collected by IBM). There are several challenges we encountered with data collection in this area, many of which we believe to be inherent in the process. The first is access to databases, many of which are behind firewalls and require multiple levels of permission to even be able to obtain the first level. Even determining which databases can give the information needed, and then whom to contact for these databases, is often not straightforward. Once at the database, the sizes and quantity of data are often such that only a few databases are able to handle them, and only on very large servers. There are data dictionaries which need to be understood and applied to the database itself, including multiple levels of acronyms and definitions. We found it useful to first study the data dictionaries, which give indicators not only of what variables are present in the database, but often in addition what types of classifications and ranges. At that point, subsets of the data can often be identified and loaded onto local machines for analysis.

There are also key variables identified for which there is no clear way to get the data, besides a comprehensive interview of either the sales teams or the clients. Interviews for the purposes of gathering data have their own challenges, particularly biases in interviewing. In many of the existing studies, the independent variables chosen are at a fairly high or abstract level, e.g., project management capability. It is very difficult to establish an objective way to measure such variables so most have chosen to collect subjective data on it through a survey. Even if we were interested in a more detailed breakdown of such a variable, the variable is impacted by so many factors that an explicit model of such a variable is a whole other study in itself. (One example is customer relationship.) For the purpose of obtaining general insight, utilizing a high level variable is adequate. One disadvantage, though, is that the subjective data may contain personal biases or estimation errors of the individual respondent.

In general our goal is to obtain as much data as possible from existing databases, and then focus on framing our analysis such that the remaining variables could be addressed by interviewing sales or marketing employees of our own company, as opposed to having to contact such professionals of another company, or having to conduct a widespread survey.

Once adequate data have been collected, the next step is to detect structural patterns and construct model fragments, using automated causal-structure discovery methods [27]. This is a new set of statistical techniques developed over the past two decades, which place the concept of causality on a firm mathematical foundation. The algorithms detect correlational patterns in data and use them to draw inferences about the underlying cause-and-effect relationships, and can be used to construct "causal graphs" in a semi-automated manner, roughly analogous to the construction of Bayesian networks. Variables for which data is unavailable or which cannot be directly measured will be treated as latent variables. They will either be estimated via the other observed variables, or scales will be devised to measure the latent variables. Structural equation modeling (e.g., [8]) and nonlinear regression techniques (e.g., [24]) will be used to estimate a model linking the variables.

3. We will assess the weak areas of the model (i.e., sections where the assumptions or data are less reliable), how well we are able to answer questions relating to the stakeholder scenarios, and what insights the model produces. Based on these initial results, we will consider designing a custom data collection effort, such as a survey if needed, to address the weak spots. We will also explore how independently managed models such as the US macro-economic model can be connected to our model to enhance its scope and power.

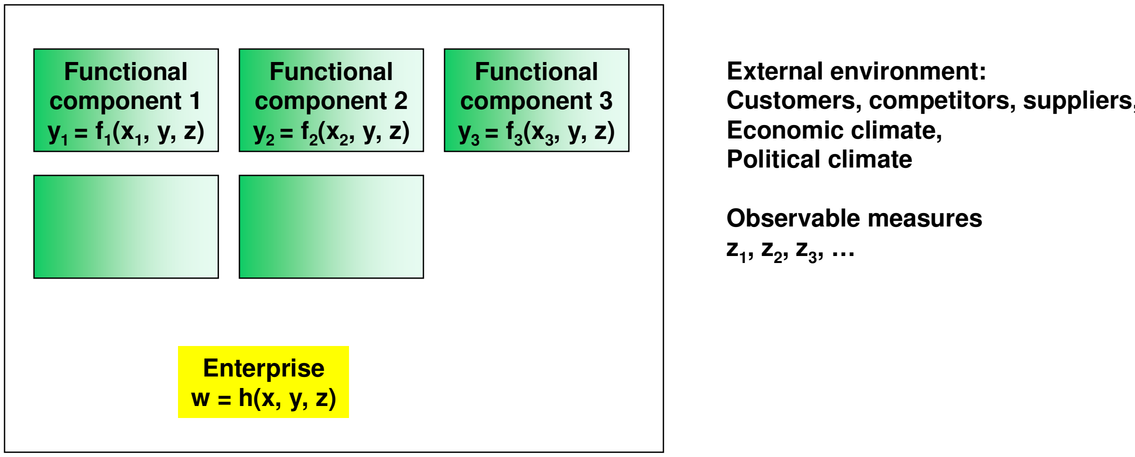
4. When a satisfactory model has been obtained (as measured by goodness of fit, variance explained, etc.) we will use it to construct a decision-support tool, possibly connected to online data sources, for use by service business executives.

## V. Conceptual Design of a Performance Model

Since a business enterprise can be complicated and the number of factors affecting its performance is large, it is useful to develop a conceptual design of the performance model to guide its detailed development. We use a fairly natural, top-down decomposition approach that views the enterprise as a composition of a set of functional components. Examples of the components are demand forecasting and planning, recruiting, information technology strategy, financial accounting, or regional marketing. The exact decomposition is dependent on the enterprise and the kind of analysis in question.

A key concept is that each component $i$ is characterized by its own performance function $y_i$ (see Figure 5.1). $y_i$ is affected by a set of causal factors, some under the control of the enterprise ($x_j$) while others are environmental variables not controllable by the enterprise ($z_k$). All the factors should be observable, otherwise a model with factors that cannot be observed or measured is not very useful as a management tool. Because the components may not be independent, in general the performance of a component may be affected by all factors across the components and the performance of all the components. However, we would like to design the model such that the components are relatively independent, so that the factors involved in the performance function of a component are largely contained in that component alone.

The performance of the enterprise, denoted by $w$ in Figure 5.1, is chosen to be the set of measures of success, as discussed in Section II. Enterprise performance $w$ is a function of the performance of the individual components $y$, the controllable variables of the components $x$, and the environmental factors $z$. There could be controllable variables $x$ at the enterprise level that do not belong to any of the components, hence $w$ is in general a direct function of $x$ as well. (The enterprise can be viewed as another component with its own controllable variables.)




**$y_i$ are performance measures of a component, $y = (y_1, y_2, y_3, \ldots)$**
**$x_j$ are controllable variables of a component, $x = (x_1, x_2, x_3, \ldots)$**
**$z_k$ are observable variables of the environment, $z = (z_1, z_2, z_3, \ldots)$**
**$w_n$ are performance measures of the enterprise, $w = (w_1, w_2, w_3, \ldots)$**

Figure 5.1. Conceptual Design of a Performance Model

To illustrate the conceptual design, Figure 5.2 shows a simplistic performance model, using gross profit as the enterprise performance measure. The enterprise is modeled by four components: service delivery, marketing and sales, business administration, and research and development (R&D). Gross profit is simply the revenue minus the total costs which include the cost of goods sold (COGS), the sales and general administrative expenses (SG&A), the research and development costs (R&D), and other costs (Other). Each cost is related to some cost measures under the components. For example, SG&A is the sum of the marketing and sales cost and the business administration cost.

Revenue is modeled by marketing spending multiplied by the market share of the enterprise. Market spending is the total value of the types of service provided by the enterprise and all its competitors. In the example, it is a function of gross domestic product (GDP), consumer confidence, some industry index of the enterprise's clients (reflecting on the general health of their industry), and the interest rate. The market share of the enterprise is a function of last year's market share (due to inertia in changing vendors), customer satisfaction of the enterprise's performance, the general reputation and presence of the enterprise in the industry, the price, features, and quality of the products and services offered by the enterprise. Each of these factors is a performance measure under some of the components. For example, the quality of the products and services offered is primarily a measure under the service delivery component. Customer satisfaction is a measure of the entire organization even though marketing and sales has the responsibility for it. For example, the lead time for service delivery contributes to customer satisfaction, and in turn the lead time in business administration tasks contributes to the lead time for service delivery.

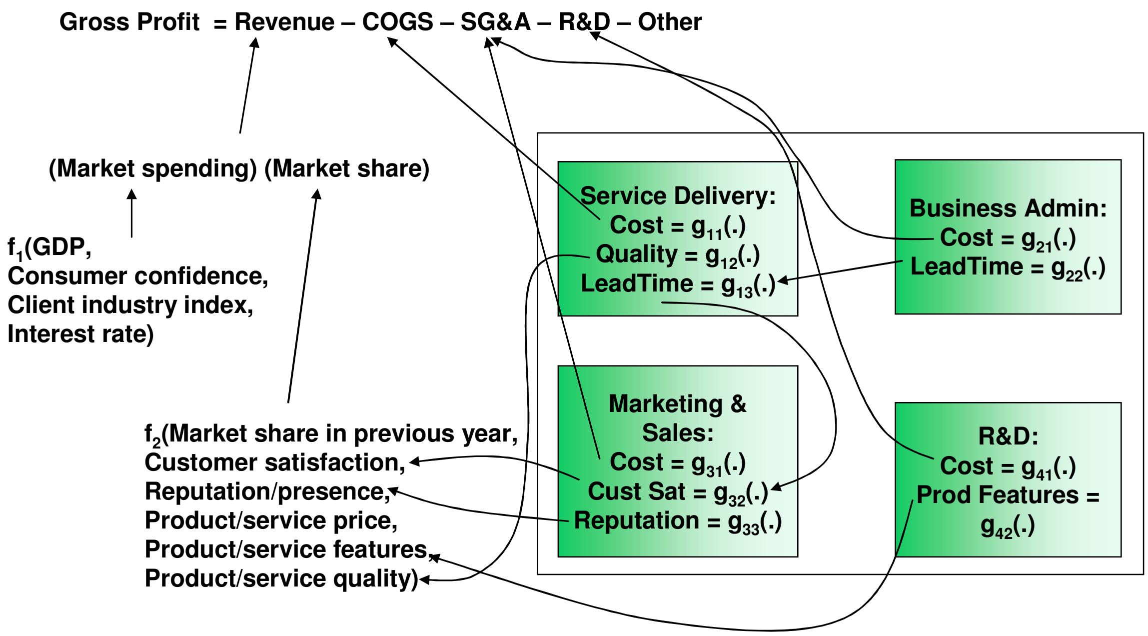



Figure 5.2. Example of a Performance Model

## VI. Concluding Remarks

Business performance in enterprises is one of the most active areas in business research and practice. In spite of so much practical relevance, the foundations of performance modeling are in its infancy. Most of the existing models involve narrow portions of the enterprise (e.g., operations such as call centers). The study of how enterprise-wide performance is affected by specific actions largely remains an art, despite the many different communities involved, e.g., business researchers, operations practitioners, business strategists, consultants, standards organizations, industry analysts, market research companies, etc. As we have found, the reasons for this scarcity is explained by one statement: modeling business performance at the enterprise level is a very difficult problem.

In effect, most business performance modeling efforts have been reduced to simplified and manageable problems in which a small number of indicators are modeled as a function of a small number of actionable variables. Usually, the variables or indicators are chosen a priori, without more rationale than the empirical fact that they are commonly used by practitioners.

Modeling business performance rigorously is one of the most important problems yet to be investigated to some depth in business research. The fact that the field is almost virgin is explained by nature of the work needed: it is a highly multidisciplinary area of work in which business research, mathematics and statistics, social sciences, and economics come to play side-by-side with practical experience. At the same time, a complete performance model for an enterprise is likely to be very large and complicated, involving many sub-models of different disciplines mentioned. Development of such a model will require substantial time and effort. This poses a difficult problem for a single research organization, in terms of the scope of skills and the investment in time and effort required. We are currently investigating the possibility of developing an open, joint approach between different organizations, similar to an open source software development effort.

We believe that business performance is an area in business research where collaboration across different ecosystems, e.g., different industries and technical areas, will bring many benefits.

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