Technology and Strategic Management Decision-Making as a Constrained Shortest Path Problem

By

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners. I understand that my thesis may be made electronically available to the public.

Abstract

A constrained shortest path algorithm is developed and implemented in Matlab to optimize the management decision-making process, which is a potential tool for managers. An empirical analysis is performed using Statistics Canada's Workplace and Employee Survey (WES), which consists of variables relating to employers and their employees, conducted from years 1999 through 2004, inclusively. Specifically, the research explores the relationships among variables such as innovation, technology use, training and human resource management and its effect on the success of the firm in terms of profit and labor productivity. The results are compared to the current literature in technology and organizational management. In general, it is discovered that optimal management strategies are highly dependent upon the performance in which the firm operates. Additionally, the constrained shortest path algorithm developed for the thesis is tested against other leading methods in the literature and is found to be quite competitive. The tests are run on randomly generated constrained shortest path problems of varying degrees of complexity with the algorithm performing well on all levels.

Acknowledgements

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1 Introduction

To create the best conditions for growth in a knowledge-based economy, firms need to fine-tune their policies on education, training, innovation, labor adjustment, workplace practices, industrial relations and industry development. The results from this research aim to clarify many of these issues and to assist in policy and organizational development.

New technology has allowed manufacturing firms to move from high-volume, low-variety production to low-volume, high-variety production. The market increasingly demands this sort of production process meaning that growth and success depend on it. The new technologies have allowed for quicker market response as well as higher product quality. This has transformed the flexibility of the firm from a competitive advantage to being the norm. Now methods of production are continually upgraded to more automated and integration-oriented techniques.

With the high cost and uncertainty involved with implementing technology and supporting organizational changes, firms need to carefully consider if, how, and when they choose to add such technologies. One technology may boost the bottom line of one firm yet destroy another firm's profit margins. Obviously if two firms are in different industries producing or offering vastly different products or services this makes reasonable sense. However, even two firms in the same industry producing or offering the same product or service could run into this particular situation. This discrepancy is predicated on several factors, including (but not limited to):

- Their products are produced via different processes, thus the technology may be used differently as well.
- Their organizational infrastructures are not the same, leaving one firm with the capability of using the technology more efficiently.
- The skill sets of one firm's pool of human capital are superior in adjusting to changes within the organization.
- One firm has more financial capital to implement the technology as well as the entire supporting infrastructure required for efficiency.

Since a specific technology and/or other organizational change must be the right 'fit' for a particular firm in order to improve success (which can be measured in many ways, such as profit, productivity, return on assets, return on investment, sales growth), all of the implementations, new and old, must work well together. The overall goal of a firm should be to maximize productivity and/or profit with respect to the possible combinations of organizational changes available. We will refer to any given combination in terms of 'state'; e.g. 'state' of operations, 'state' of organizational changes, or 'state' of business practices, etc.

Given the statistical means[1] relating to profit and/or labor productivity of firms in each industry and size class, it would be useful to give particular firms a suggested 'optimal route' from their current state of operations to their theoretical optimal state. This could be done by using their particular size class and industry as a guiding point.

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[1] Statistical means are calculated using the following variables:

$$\text{Profit} = \frac{\text{Total Revenue} - \sum(\text{Total Implementation Costs})}{\text{Total Number of Employees}}$$ and

$$\text{Labor Productivity} = \frac{\text{Total Value Added}}{\text{Total Number of Employees}}$$, averaging over all survey respondents over all years 1999-2004 as well as over each industry..

Depending on the assumptions, an appropriately modified shortest path algorithm can be implemented to give a step-by-step list of changes to be made by a firm to reach its highest potential.

To optimize the operational strategy of a firm given its current state, there are several approaches that may be considered, depending on the limitations and preferences of the firm. The following are a short list of some of the possible restrictions that may be binding:

- Limited financial capital to make the organizational changes
- Limited amount of time to make the organizational changes
- A limit to the number of organizational changes allowed by the manager, firm or union
- Other internal policies which restrict implementation

If there were no restrictions and if making changes to one state of a given set of technologies to another only resulted in a net loss to implement (instead of a net profit, obtained by such methods as selling equipment when removing a technology), a simple Dijkstra's algorithm could be implemented to find the shortest path from the starting state of the firm to the state that exhibits the greatest profit[2]. If there did exist negative valued arcs in the graph, then a more generalised shortest path algorithm would be needed, such as the Bellman-Ford dynamic programming algorithm.

By using Dijkstra's algorithm or the Bellman-Ford algorithm, the result would be the least-cost set of one-step-at-a-time organizational changes to get to the optimal state of operations. If, however, the cost of implementation is not of a concern, then the graph

[2] Using the mean profit as previously defined.

could be constructed where each arc (i.e. one-step organizational change) is given a unit value, so that when a shortest path is computed, the optimal path will result in the least amount of changes necessary to achieve the optimal state.

In the case of limited financial capital, Dijkstra's algorithm would need to be modified so that any paths that exceed the maximum capital available would be disregarded. Since the optimal ending state may be unattainable, all shortest paths from the starting state to every other state should be computed. Then the path that contains the highest attainable operational state as its ending state is the optimal path to the problem. This could be generalized to multiple resource constraints or other restrictions.

Thus, the most interesting and generalizable solution to the problem would be to find the shortest path with multiple edge weights (which could include various resource costs) and weight limits. This kind of a problem is referred to as the constrained shortest path problem (CSPP). Even with non-negative edge weights this problem is shown to be NP-complete (Gary and Johnson, 1979). Simple shortest path problems with non-negative edge weights can easily be solved in polynomial time when each edge contains only one weight and there are no restrictions on the path. Thus, this thesis focuses on the more difficult CSPP problem for the case of finding the optimal organizational changes of a given firm.

Evolutionary economic theory provides us with a framework to discover if the order of adoption (and further use or rejection) of organizational practices could be correlated to the overall growth and prosperity of the firm. This suggests that in terms of adoption, path-dependency may well be crucial in helping to explain effects of adoption choices. Path-dependence explains how the set of decisions a firm faces for any given conditions (such as market conditions or organizational choices) is limited by the decisions the firm has made in the past, even though past conditions may no longer be relevant. Thus, in theory, organizational practices that are made may be dependent on the period in which they are implemented as well as the order of implementation.

By identifying optimal paths, in this thesis, we are thereby discovering an evolutionary path-dependent solution for a firm in order to achieve a theoretical maximum performance in the smallest number of organizational changes based on empirical evidence.

1.1 Benefits of Research

Managers can use the results and/or the algorithms presented as a roadmap for planning a successful implementation of organizational changes and business practices in their organization, based on their given metric, whether that involves profit, productivity, growth, or some combination of them. The study also allows managers to review previous operational adoptions and gain knowledge as to why those implementations may have worked or failed. Also, the framework used in the study can be further extended to optimize their business according to alternative objectives, such as employee retention and capital input.

Since the empirical sample covers firms nation-wide, the results could be used by Canadian government agencies to aid in future policy decisions, such as tax incentives, that encourage efficient growth of the nation's economy as a whole. Finally, this work adds to current literature in organizational management and evolutionary economics as another method of empirical analysis for technology, innovation, human resource management, and other organizational factors within the workplace.

It should be noted that this thesis examines correlations between performance levels of firms and their organizational practices. Thus, causality is not inferred in this analysis. In addition, the thesis is static; that is it does not consider interdependence between firms in an industry, such as in a game theoretic model.

2 Literature

2.1 Technology, Innovation, Workplace Practices and Performance

Recent technologies and changing workplace practices have altered the nature and organization of work. There have been many stories in the popular press about the successes associated with the introduction of high-performance workplace systems and the revolution computers have caused on the job. At the same time, the gains to completing a college degree relative to a high school diploma have doubled over the past fifteen years in response to what many have argued are the skill demands associated with new technologies and changing work organization.

2.1.1 Computer Technology

The rapid and continuing decline in the cost of computing and increases in the power and variety of computer systems are an exogenous and powerful change in the environment of the firm. As computers have become faster, smaller, cheaper, more flexible, and easier to network together, the quality-adjusted real price of computers has been declining at a compound rate. These changes and similar changes in technical complements to computers lead to very rapidly growing demand for IT. The growth in demand means that firms must regularly readjust their computer capital stocks.

The progress of IT investment at the firm level is not, however, smooth and direct. A substantial case- and interview-study based literature[3] and a smaller

[3] See, for example, Applegate, Cash, and Mills (1988), Attewell and Rule (1984), Barras (1990), Crowston and Malone (1988), Davenport and Short (1990), David (1990), Malone and Rockart (1991), Milgrom and Roberts (1990b), Autor, Levy, and Murnane (1999), Scott Morton (1991), and Zuboff (1988).

econometric one[4] have examined the causes of variety across firms in the pace and success of IT adoption. It points to complementarities among the use of computers, workplace organization, and output characteristics.

Surveys of managers and the case-study literature show that the most important reasons for investing in IT are product quality improvements, notably customer service, timeliness, and convenience (Brynjolfsson and Hitt, 1995, 2000). Flexible machinery and organizational structures can efficiently supply a highly varied output mix (Milgrom and Roberts, 1990a). Organizational changes set off by IT investment are intended either to reduce cost or to improve product and service capabilities, although the latter is typically more important (Hammer, 1990; Davenport and Short, 1990; Brynjolfsson and Hitt, 2000). Similarly, the combination of organizational and technological innovation is required to deliver consistently high levels of customer service (Davenport, 1994). All this suggests a three-way cluster of complementarity among product quality improvements (broadly understood), reorganization, and IT investment.

While inventions that lead to improvements in IT are quickly available throughout the economy, complementary organizational changes involve a process of coinvention by individual firms (Bresnahan and Greenstein, 1997). Identifying and implementing organizational coinventions is difficult, costly, and uncertain, yielding both successes and failures. These adjustment difficulties and the experimentation and coinvention surrounding IT use leads to variation across firms in the use of IT, its organizational

[4] See Ito (1996), Bresnahan and Greenstein (1997), and Brynjolfsson and Hitt (1997).

complements, and the resulting outcomes. The presence of adjustment costs for IT is well supported by both case studies and statistical analyses.[5]

2.1.2 Innovation and Training/Education

Brenahan, Brynjolfsson, and Hitt (2002) found that IT, complementary workplace reorganization, and new products and services constitute a significant skill-biased technical change affecting labor demand in the U.S. They also found that firms that adopt these innovations tend to use more skilled labor. The effects of IT on labor demand are greater when IT is combined with specific organizational investments.

2.1.3 Computers & Training/Education

There is evidence that computers and skilled labor are relative complements in data at the industry level (e.g., Autor, Katz, and Krueger, 1998; and Berman, Bound, and Griliches, 1994) and establishment level (e.g., Doms, Dunne, and Troske, 1997; and Black and Lynch, 2001).

2.1.4 Computer Use, Performance, and Innovation

Early on, computers were hailed as a revolution that would change professional work. Many users have computer skills but as the technology is continuously changing

[5] Systematic statistical work on shifts in computing architectures has found substantial adjustment costs (Ito 1996; Bresnahan and Greenstein 1997), and the case literature on IT implementation highlights difficulties in implementing concurrent organizational changes (e.g., Kemerer and Sosa (1991) and Zuboff (1988)). Moreover, there is additional evidence that monetary and nonmonetary costs of these adjustments are larger than the capital investments in many cases (Bryniolfsson and Hitt 1996; Brynjolfsson and Yang 1997; Bresnahan 2000).

computer-user education and training is one of the primary issues concerning educators and businesses (Guimaraes and Ramanujam, 1986). The broad diversity of individuals among the trainees, even in the same organisation can be problematic. This suggests that other organizational changes may be necessary to fully utilize the potential benefits of new technology.

Brynjolfsson & Hitt (2003) found evidence that computerization contributes to productivity and output growth in large firms. They also discovered that computerization is not simply buying computer capital; instead it involves a broader collection of complementary investments and innovations, some of which take years to implement. So although computer investment generates useful returns in its first years of service, greater output contributions accrue over time. Their result implies that the long-term growth contribution of computerization represents the combined contribution of computers and complementary organizational investment, such as training.

2.1.5 IT & Products

Bartel, Ichniowski, and Shaw (2007) found that in manufacturing, plants that adopt new IT-enhanced equipment also shift their business strategies by producing more customizable products. Also, new IT investments improve the efficiency of all stages of the production process by reducing setup times, run times, and inspection times. The reductions in setup times can make it less costly to switch production from one product to another and support the change in business strategy to more customized production. Also, adoption of new IT-enhanced capital equipment coincides with increases in the skill requirements of machine operators, notably technical and problem-solving skills, and with the adoption of new human resource practices to support these skills.

2.1.6 Human Resource Management

The desire of human resource (HR) practitioners to demonstrate the value of what they do for the rest of the organization has a long history. Drucker (1954) referred to "personnel" managers as constantly worrying about "their inability to prove that they are making a contribution to the enterprise," (p. 275). This has been echoed more recently by Tom Stewart, who described HR leaders as being "*unable to describe their contribution to value added except in trendy, unquantifiable and wannabe terms…"* (Stewart, 1996, p. 105).

In response to these longstanding and repeated criticisms that HR does not add value to organizations, in recent years burgeoning of research attempted to demonstrate that progressive HR practices result in higher organizational performance. Huselid's (1995) groundbreaking study demonstrated that a set of HR practices he referred to as high performance work systems (HPWS) were related to turnover, accounting profits, and firm market value.

Since then, a number of studies have shown similar positive relationships between HR practices and various measures of firm performance. For instance, MacDuffie (1995) found that "bundles" of HR practices were related to productivity and quality in his sample of worldwide auto assembly plants. Delery and Doty (1996) found significant relationships between HR practices and accounting profits among a sample of banks. Youndt, Snell, Dean, and Lepak (1996) found that among their sample of manufacturing firms, certain combinations of HR practices were related to operational performance indicators. More recently, Guthrie (2001) surveyed corporations in New Zealand and found that their HR practices were related to turnover and profitability. This vein of research has been summarized by Huselid and Becker who stated "Based on four national surveys and observations on more than 2,000 firms, our judgment is that the effect of a one standard deviation change in the HR system is 10–20% of a firm's market value" (Huselid & Becker, 2000, p. 851).

In recent years, there has been growing interest in the economic and managerial literature in so called "high performance work practices” (HPWPs), such as total quality management, formal teams, job rotation, and employee involvement programs. Such practices aim to assure greater flexibility and motivation of the workforce, to increase the participation of workers in decision-making, and to take advantage of their problem-solving and communication skills. So their adoption by firms allegedly results in better economic performance. Massimo, Delmastro, and Rabbiosi (2007) suggest that the adoption of HPWPs leads to better performance, especially when it is associated with the delegation of decision authority down the corporate hierarchy.

Black and Lynch (2001) found that unionized establishments that have adopted human resource practices that promote joint decision making coupled with incentive-based compensation have higher productivity than other similar nonunion firms, whereas unionized businesses that maintain more traditional labor management relations have lower productivity. They also found that firm productivity is higher in businesses with more-educated workers or greater computer usage by nonmanagerial employees and that allowing greater employee voice in decision making is what seems to matter most for productivity. Also, instituting a profit-sharing system is effective, but only when it is extended to nonmanagerial employees.

'Human Capital'

There are three main components of 'human capital' — early ability (whether acquired or innate); qualifications and knowledge acquired through formal education; and skills, competencies and expertise acquired through training on the job.[6] The concept of human capital arose from a recognition that an individual's or a firm's decision to invest in human capital (i.e. undertake or finance more education or training) is similar to decisions about other types of investments undertaken by individuals or firms. Human capital investments involve an initial cost (tuition and training course fees, forgone earnings while at school and reduced wages and productivity during the training period) which the individual or firm hopes to gain a return on in the future (for example, through increased earnings or higher firm productivity). As with investments in physical capital, this human capital investment will only be undertaken by the wealth maximising individual or firm if the expected return from the investment (or internal rate of return)[7] is greater than the market risk adjusted rate of interest.

(a) Measuring the Impact of Education and Training

There are several problems that arise when trying to estimate the true causal effect of education and training on individual earnings. The most discussed of these is the issue of

[6] Other labor market activities that are sometimes included in the concept of human capital include migration and search for new jobs.
[7] The return is a net figure as it takes into account the costs to the individual or firm of the human capital investment.

whether the higher earnings that are observed for better educated or highly-trained workers are *caused* by their higher education or training, or whether individuals with greater earning capacity and ability choose to acquire more education or training[8]. If the latter is true, then simple estimates of the return to education or training will be too large, as they will be unable to separate the contribution of unobserved ability from that of education and training and will ascribe them both to education and training (so-called 'ability bias'). Conversely, if education or training is measured with error, the estimates will be too small. Different methods have been developed and applied to account for some of the potential biases that may arise.

(b) Estimates of the Returns to Education

Empirical results do suggest, in line with the theoretical literature, that education confers significant wage advantages to individuals. Most of the early studies of the returns to education ignored such things as ability and measurement error bias, whereas the more recent literature has placed much more emphasis on attempting to control for these potential problems. Most empirical studies also ignore the direct and indirect costs of education because of the difficulties involved in measuring these costs (and thus measure *gross* rather than *net* returns). Studies that have accounted for the direct and indirect costs of education show positive net internal rates of return as well.

(c) The Determinants and Effects of Training

In most empirical studies, training is distinguished from formal school and post-school

[8] This is a form of signaling as discussed in Spence (1973).

qualifications (which are viewed as education) and is generally defined in terms of courses designed to help individuals develop skills that might be of use in their job.[9] What is clear from studies looking at the returns to training and participation in training is that using highly-aggregated descriptions of 'training' misses important differences in the determinants and effects of different forms of training.[10]

The Relationship between Education and Training

Given that the benefits of work-related training are quite large (Blundell et al, 1999), it is of interest to establish what sorts of individuals receive this training. What is clear from almost all of the studies looking at the determinants of training is that individuals with higher ability (as measured by aptitude scores), with higher educational attainment, who have undertaken training in a previous period (with the current or even a former employer) or with higher occupational status and skills are significantly more likely to participate in training.

A picture emerges of a strong complementarity between the three main components of human capital — early ability; qualifications and knowledge acquired through formal education; and skills, competencies and expertise acquired through training on the job. The current accumulated stock of human capital provides both strong incentives and more opportunities for further investments in human capital formation, thus highlighting the self-sustaining nature of individual human capital growth.

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9 This is not always true. For example, in the study by Green (1993) using data from the UK General Household Survey, training includes 'self-instruction' which includes activities such as 'teaching yourself to use a word processor over a period of time'.

10 See Blundell, Dearden and Meghir (1996).

2.1.7 Innovation

Radical innovations have captured the attention of both researchers and policy makers who each in their own way have looked for answers to the crucial question: "What can be done to foster radical innovations?" (Green et al., 1995; Cooper and Kleinschmidt, 1996; Freeman and Soete, 1997; Danneels and Kleinschmidt, 2001; Darroch and McNaughton, 2002; Chandy et al., 2003; Sorescu et al., 2003; Kenny, 2003). Radical innovations are important because they improve competitive advantage and create opportunities for firms to open new markets (Lynn et al., 1996; McDermott and Handfield, 2000; McDermott and O'Connor, 2002).

For firms, the decision to attempt the discovery of radical innovations carries significant implications. In fact, this type of innovation is associated with higher risks and more management challenges than the development of incremental innovation (O'Connor and Veryzer, 2001). Prior studies on radical innovation also suggest that it requires more resources, mainly financial and human resource as well as research knowledge (Stringer, 2000).

Although there is an expanding body of conceptual and empirical studies on radical innovation, the studies tend to suffer from many methodological problems (Sorescu et al, 2003). For example, the problems are associated with the composition of the study population, the specification of the dependent variable "radical" innovation, the failure to report and explain what is "radical" in radical innovations and the choice of the independent variables. Some of these methodological problems are due to the fact that, despite several attempts to develop conceptual models to explain radical innovation (Garcia and Calantone, 2002), there is not as yet a consensus.

Strategic HRM still lacks an appropriate and robust theoretical framework, not to mention the associated methodological difficulties that exist in the area. In addition, insufficient attention is being paid to its practical implications and development for decision makers (Paawe and Richardson, 1997). Unresolved debates occur around so-called best practice models versus contingent, resource-based and firm-specific approaches. This underlines the difficulty in establishing robust directional or cause-effect relationships between variables in survey research. Empirical results are largely based on the framework shown in the figure below (Paawe and Richardson, 1997). This framework proposes a cause-effect relationship between firm performance and human resource management (HRM) activities. Better performing firms therefore are more likely to invest more in human resource development (HRD).

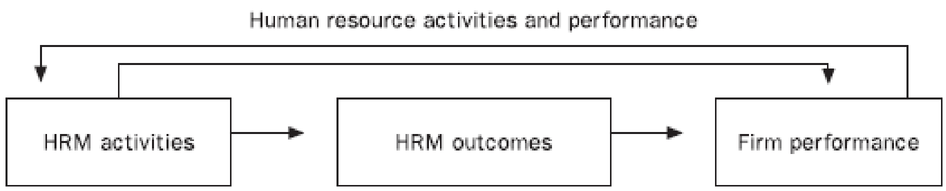

Figure 1. A cause-effect relationship between firm performance and HRM activities

Strategic approaches to HRD can be differentiated from traditional approaches. Key features of strategic human resource development (SHRD) practices include:

- integration into a human resource strategy, which in turn is aligned with an organizational or corporate strategy;

- competency based HRD derived from structural, systemic, technological and work re-organization needs; this in contrast to menu offerings by centralized training departments in large organizations;
- line management responsibility for developing people is a key performance area in the appraisal and reward of a manager;
- partnership between HRD specialists and line managers in developing employee competencies required to achieve organizational performance goals;
- creating an organizational culture of continuous learning and transfer of learning between units;
- measuring and evaluating the effectiveness of HRD practices on individual, team and work unit performance (this is probably one of the most critical components of SHRD - the HRD profession has not found a generally acceptable methodology for evaluating the transfer of training and its effectiveness in the work place, which is a large and fundamental gap, limiting the extent to which HRD can be recognized as playing a strategic organizational role);
- targeting value - adding performance areas for specific development initiatives, which potentially enhance competitive advantage - these include service excellence, product innovation, creative problem solving, leadership and team development;
- business and work process integration - this involves learning to work collaboratively across traditional functional disciplines in multi-functional/disciplinary teams, which requires both new interactive skills and organization redesign. Executive development programs increasingly emphasize

> integrated managerial and organizational processes. This requires learning in multi-functional flexible teams, rather than a ``functional silo" pre-occupation, where development is solely an individual rather than collaborative learning process. Depending on contingency requirements at the time, SHRD focuses variously on development at several levels (Figure 2).

Allocation of HRD resources, expenditure and effort vary at different levels depending on strategic priorities over time. Often a misallocation occurs, resulting in training efforts which add little value to an organization. This underlines the need to develop a methodology which evaluates the degree of fit/alignment between HRD practices and organizational goals. HRD specialists, line managers and external management educators need to collaborate actively to find relevant measures for following up on the effectiveness of development processes.

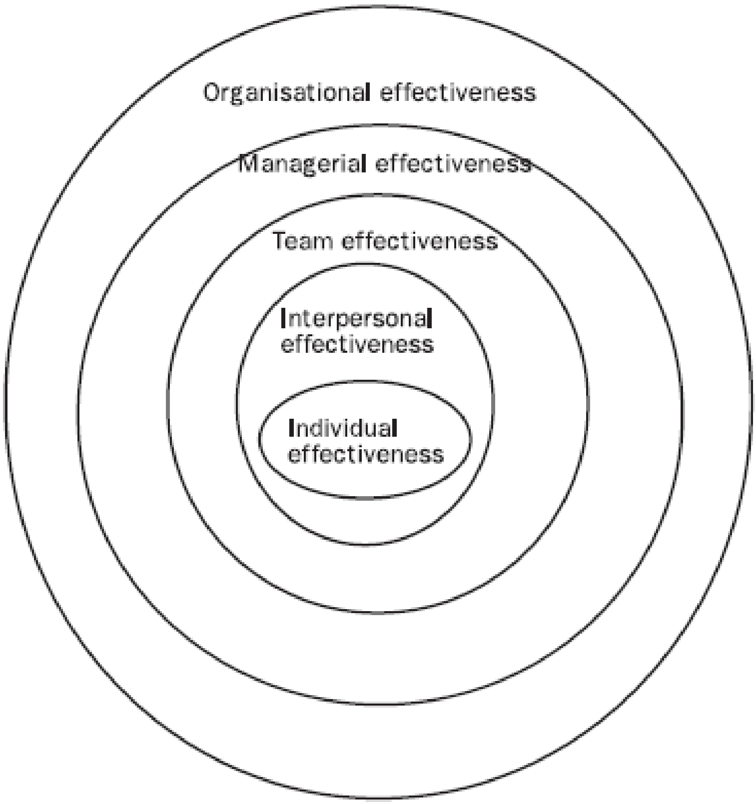

Figure 2. Levels of Human Resource Management

Figure 3 below illustrates factors driving a strategic approach to HRD. Features of this approach include explicit and accountable links to business strategy, executive management endorsement and commitment as well as that of other organizational stakeholders, a recognition at a strategic level that organizational capacity is a function of the competency and capabilities of its people, and executive requirements for information reporting and monitoring of HRD practices and effectiveness. The strength of the HRM system can help explain how individual employee attributes accumulate to affect organizational effectiveness.

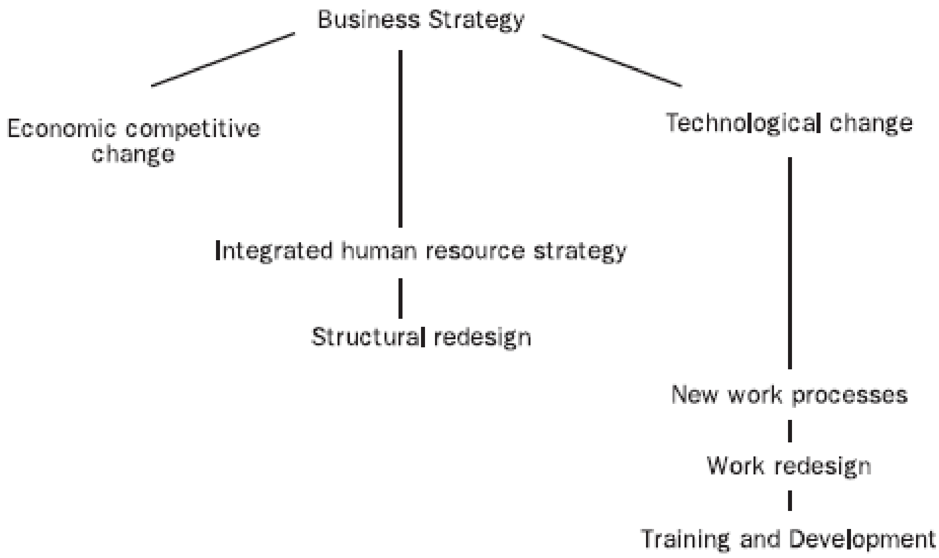

Figure 3. Strategically linked human resource development

In recent years scholars have devoted a great deal of attention to examining the linkage between HR practices and firm performance. Based on research evidence to date, it is becoming increasingly clear that the HR system is one important component that can help an organization become more effective and achieve a competitive advantage (Becker & Huselid, 1998). However, a larger question remains unanswered: *How* does HRM contribute to firm performance?

In research on the HRM–firm performance relationship, scholars have often assumed two perspectives. One has been based on a systems approach. Research in this area has moved from a focus on *separate* HRM practices and *employee* performance to a more macro focus on the overall *set* of HRM practices and *firm* performance (e.g., Arthur, 1992; Huselid, 1995; Huselid & Becker, 1996; Huselid, Jackson, & Schuler, 1997). That is, the dominant trend in research on the HRM–firm performance linkage has been to take a systems view of HRM by considering the overall configuration or aggregation of HRM practices (Ferris, Arthur, Berkson, Kaplan, Harrell-Cook, & Frink, 1998), rather than by examining the effects of individual HRM practices on firm performance (e.g., Delaney & Huselid, 1996; Delery & Doty, 1996) or on individual performance.

A second approach has been the strategic perspective on HRM, which has taken on different meanings in the literature (Ferris et al., 1999). In one strategic-based approach, researchers have examined the particular "fit" between various HRM practices and the organization's competitive strategy (e.g., Miles & Snow, 1994; Wright & Snell, 1991). Embedded in this view is the notion that organizations must also horizontally align their various HRM practices toward their strategic goal and that practices must complement one another to achieve the firm's business strategy (Schuler & Jackson, 1987a,b; Wright & Snell, 1991; Wright, McMahan, & McWilliams, 1994). The guiding logic is that a firm's HRM practices must develop employees' skills, knowledge, and motivation such that employees behave in ways that are instrumental to the implementation of a particular strategy. Similarly, researchers have taken a contingency perspective, with the assumption that the effectiveness of the HR system depends on contextual features such as industry, firm size, or manufacturing policies (e.g., MacDuffie, 1995; Youndt, Snell, Dean, & Lepak, 1996).

A related approach within the strategic perspective on HRM pertains to how the overall set of HRM practices is generally associated with firm performance and competitive advantage (Ferris et al., 1999). Central here is the resource-based perspective (Barney, 1991) such that, collectively, a firm's human resources are believed to have implications for firm performance and provide a unique source of competitive advantage that is difficult to replicate (Wright et al., 1994). The guiding proposition is that HRM practices are socially complex and intricately linked in ways that make them difficult for competitors to copy (Boxall, 1996). More fully, the complexities of the human resource value creation process make HRM a source of competitive advantage that is rare, inimitable, and non-substitutable (Barney, 1991; Ferris et al., 1999). The resource-based view has prompted recent work on how HRM practices contribute to firm performance by leveraging human capital, discretionary effort, and desired attitudes and behaviors (e.g., Becker & Gerhart, 1996; Lado & Wilson, 1994; Wright et al., 1994).

Taken together, these two perspectives on the HRM–firm performance relationship—the systems and strategic perspectives—help stage how HRM practices and their influence on employee attributes can lead to desired outcomes at the firm level, such as productivity, financial performance, and competitive advantage. Yet still left unanswered is the process through which this occurs. Although both perspectives take a macro approach, they assume implicit, multilevel relationships among HRM practices, individual employee attributes, and organizational performance (Huselid, 1995; Wright et al., 1994). The features of HRM that are necessary to facilitate these linkages have not been well addressed.

2.1.8 Evolutionary Economics

Evolutionary economics is essentially the study of changes in generic knowledge, and involves transition between actualized generic ideas. It is a heterodox school of economic thought that is inspired by evolutionary biology. Much like mainstream economics, it stresses complex interdependencies, competition, growth, structural change, and resource constraints but differs in the approaches which are used to analyze these phenomena. Evolutionary economics makes extensions to key areas of classical and neoclassical economics.

The evolving economic system presumes to be composed of subject and object rules (or routines), such as with classical and neoclassical theories. In addition, it assumes that these rules are not universal and invariant, but can change. In essence, evolutionary economics does not take the characteristics of either the objects of choice or of the decision-maker as fixed. Rather its focus is on the processes that transform the economy from within and their implications for firms, institutions, industries, employment, production, trade, and growth. The processes in turn emerge from actions of diverse agents with bounded rationality who may learn from experience and interactions and whose differences contribute to the change. The subject draws on the evolutionary methodology of Charles Darwin. It is naturalistic in purging earlier notions of economic change as teleological or necessarily improving the human condition (Witt, 2008). This method of thinking seems prudent, especially in regards to the area of technology management since innovation (and particularly radical innovation) often destroys market equilibrium and thus forces adaptation and change among firms.

The evolutionary theory of the firm provides an alternative explanation of the firm based on routines. While it is true that the evolutionary theory focuses especially on the technological aspects of production, it also stresses the cognitive nature of the organizational structure of the firm. The evolutionary theory of the firm in its original form as proposed by Nelson and Winter (1982) is similar to the 'black-box' view of neoclassical economics a device to study evolutionary dynamics. This view of the firm does not consider the organization of the firm in an explicit way. However, the firm is described as entity processing, storing and producing knowledge. Evolutionary economics sees the economy as a scientific domain characterized by disequilibrium processes in which economic agents create and adapt to novelty through learning rather than a system in equilibrium or resting in a steady state (Witt 1991, Nelson 1995, Saviotti 1997, Foster and Metcalfe 2001, Fagerberg 2003, Cantner and Hanusch 2002).

The framework outlined in Nelson and Winter's contribution has proved to be fruitful, especially in the area of economics of technology and growth theory. Three distinguishing and interrelated traits of evolutionary economics are:

1. *Knowledge and information* as the central theme. Economic systems are knowledge-based. Economic knowledge is conceived as set of routines that are reproduced through practice. The processes of knowledge creation and destruction underpin and drive economic growth and qualitative change. The growth of knowledge cannot be meaningfully captured as a constellation of equilibrating forces (Nelson and Winter 1982, Metcalfe 1998, Witt 1997, Foster and Metcalfe 2001).
2. *Population approach* (as opposed to a typological) is used. The heterogeneity of economic behavior is based on the distribution of knowledge and information within the economy (Hayek 1945). Heterogeneity drives economic change, which can cast in terms of observable changes in the compositions of population of firms, technologies, and industries. The decentralized nature of the economic system implies that there is massive parallelism of computation and behavior

within the economic systems. Together with spillovers the decentralized organization creates not only the problem solving capability of the economic system but also the capability to formulate new problems and new behavior (Dosi 1997, Metcalfe 1998).

3. The *interdependence between selection and development* is focused upon. Competition as selection process provides a process structuring economic activity (Metcalfe 1998) and imposing a requirement of procedural rationality on participants (firms). Selection processes operate on variety and they destroy variety. The generation of variety and the selection of variety interact in the process of development. In order to have economic development, variety needs to be re-created.

The specific feature of the evolutionary approach is that it explains the adaptive behaviors of firms through the tension between innovation and various selection mechanisms. Coriat and Weinstein (1995) argue that an evolutionary theory of the firm has the advantage, compared to other theories of the firm, to provide an explanation for three issues of importance to understand the nature of firms:

1. It explains how a firm can be defined: through the set of routines and competencies that the firm encompasses.
2. It explains why firms differ: because they rely on a different set of routines which are firm-specific and cannot be transferred at low cost.
3. It explains the dynamics of firms: through the combined mechanisms of searching and selection and the possibility of transforming a set of secondary routines into the core activity.

In terms of conducting research and developing methodologies in practice, Malerba (2006) stresses that using methodology that is quite common to researchers in the Schumpeterian (1942) and evolutionary tradition is key:

1. identify some empirical regularities, stylised facts or puzzles that need to be explained,
2. develop appreciative theorizing,
3. do quantitative analyses and then
4. build formal models, which in turn feed back to empirical analysis in terms of tests, insights and questions.

Path-Dependency

Path dependency, a further branch of economic evolutionary theory, has been studied in relation to technological development (e.g., Dosi 1982, David 1985, 1986, Witt 1997, Rip and Kemp 1998) and research on the evolution of economic, legal or other social institutions (e.g, North 1990, Stark 1992, Bebchuk and Roe 1999, Pierson 2000, Beyer and Wielgohs 2001, Deeg 2001, Heine and Kerber 2002, Schmidt and Spindler 2002, Crouch and Farrell 2004, Ebbinghaus 2005), and continues to grow as a field.

The classical theory of path dependency assumes that initially decisions are open to revision, but from a certain point in time onwards, decisions taken increasingly restrain present and future choices. As a result, decisions that have been taken in the past may increasingly amount to an imperative for the future course of action. However, the full explanatory power path dependency theory has to offer only become s clear when two concepts are introduced in addition to the “history matters” principle: increasing returns and lock-ins. Path dependence cannot be fully explained by “past-dependence” (Antonelli 1999).

In its most general sense, the concept of increasing returns implies positive feedback, i.e. that the increase of a particular variable leads to a further increase of this very variable (Arthur 1989, 1994). More specifically, the notion of increasing returns refers to a self-reinforcing process with a spiral form of dynamics that is beyond the control of the individual firm and may eventually lead to a “lock-in” (David 1985) or “inflexibility” (Arthur 1989). When a lock-in occurs, other alternatives cease to be feasible.

Path dependency is essentially a dynamic theory with different stages. Building on the theoretical explanations by Arthur and David, three phases of a path-dependence process can be distinguished:

1. *Pre-formation phase.* This involves an undirected search process, so choices are unconstrained. Once decisions have been made, dynamic self-reinforcing processes may be set into motion and can lead to deterministic patterns. This moment of setting the path dependency into motion represents a “critical juncture” (Collier and Collier 1991). At this point the firm would enter into phase 2.
2. *Path formation phase.* Options are increasingly narrowed to an extent that firms eventually do not seem to have a choice anymore. In this case a self-reinforcing process develops that is likely to become essentially governed by the regime of increasing returns (Arthur 1994). If such reinforcing events culminate in a critical mass, the momentum has built up. In other words, a path emerges and renders the

whole process more and more irreversible, until a lock-in occurs, entering the firm into stage 3.

3. *Path dependence phase.* One particular concept (or organizational strategy in this case) has been generally adopted. Viable alternatives are no longer at hand.

When increasing returns to adoption matter, small events, such as occasional adoptions or changes in the sequences, introduction of new standards, especially if they take place at the onset of the process, may have long lasting, path-dependent effects on the eventual diffusion and especially on the outcome of the selection, in the market place, among competing and rival technologies (David, 1985, 1987, 1988, 1990).

The idea behind path dependency in relation to this thesis is that by using empirical analysis, we can create paths for firms to break out of this dependence (phase 3). In essence, the modelling done would allow a firm to set a new path or un-lock their path dependency and search for a possibly more fruitful path to follow in the future. This would be analogous to re-entering the pre-formation phase.

Industries

It's been shown that industries follow specific dynamics of innovation, firms' entry and growth and market structure, as the industry life cycle tradition (Abernathy-Utterback,1978; Utterback,1994) shows. It's also known that these dynamic sequences are different from one industry to another (Klepper,1997). The cases of specific industries provides interesting examples. In chemicals Arora and Gambardella (1998) have discussed the long run coevolution of technology, organization of innovative activities and market structure, and Murman (2003) has examined the joint interrelated evolution of the dye technology, the population of firms and market structure, national organizations (such as universities and firms), and the international leadership and decline of specific countries.

In computers, coevolutionary processes involving technology, demand, market structure, institutions and firms' organization and strategies have differed greatly in mainframes, minicomputers, personal computers and computer networks, involving different actors, mechanisms, entry processes and producer-customers relationships (Bresnahan-Malerba,1999).

We would like to empirically examine what differences, if any exists between industries in terms of their theoretical optimal paths of organizational and technological evolution created using the shortest path algorithm.

Innovation and Technology Adoption

Consistently, empirical evidence confirms that firms who engage in research and development activities are more prone to adopt new technologies, and this seems more relevant when the technologies under scrutiny imply adjustments in firms' production process, (Faria et al., 2002, 2003). In our research, this would

The adoption of a new technology is considered part of a broader process of technological change. Firms are reluctant to change their technology and are encouraged to introduce new technologies only when a clear inducement mechanism is put in place. As soon as the routines in place and hence the technology currently in use are being questioned, and the inducement mechanism has been initiated by some mismatch between plans and facts, the choice between the introduction of original technologies invented-here, and the adoption of not-invented-here technologies can take place (Antonelli, 2006).

A trade-off between technical change and technological change emerges whether to change just the technique or changing the technology. The trade-off will be tilted towards the introduction of technological changes when the access to knowledge is easy and conversely switching costs (Antonelli, 2006). Presumably, from our analysis, we could see where switching costs are generally lower for new technology adoption. In this case, we should discover that technology is adopted more for firms in those industries.

In general, we would like to further examine whether the preceding studies' results hold true in our analysis. Specifically we would be interested in observing whether our shortest path models suggest that supporting organizational strategies, such as innovation, are adopted before new technology is adopted.

Dynamic Capabilities (supporting organizational structure: e.g. Education, Training, HRM practices)

Firm capabilities and structure must be in tune with dynamic capabilities of the firm in order to prosper appropriately. Teece, Pisan, and Shuen (1990) gives a summary of many works that suggest the common theme of the firm should be on its specific dynamic capabilities.

While changing formal organization is considered relatively easy, and selloffs and buy-ups are also possible, changing the way a firm makes decisions and follows through on them is time consuming and costly (Nelson (1991). Also, it is a lot of work to get a new structure in shape and running smoothly. Thus, when a major change in strategy needs to be accompanied with a major change in structure, making these changes can take a considerable amount of time.

Firms need to learn how to create certain types of innovation and the supporting aspects to take advantage of them, and this should be done in a concentrated way rather than a hit-and-miss strategy of efforts, if possible. Then the current innovations can be the starting points towards creating and learning new innovations that advance and complement the firms' current innovations. This learning could be done through training, hiring highly educated employees, and further enhanced though some of the human resource management practices (HRM), such as information sharing among employees. This would infer that employing HRM practices, along with highly trained employees would foster an innovative environment.

There have been studies on the way technology advances, more so than studies on the way firm organization changes as in the way Chandler (1966) describes it. He says organization is strategy and structure, the things that are wider and more durable than the technologies and other routines it uses from day to day, or even the core capabilities that push the internal evolution of the firm.

What appears to have mattered most has been organizational changes needed to enhance dynamic innovative capabilities. Reich (1985), Hounshell and Smith (1988) among others have described how firms have been able to have research labs separated from regular activities of the firm so that they can work on creating new innovations for products and processes.

The moral of the literature appears to be that a dynamic work environment enhances innovation and technology. This would infer that adopting human resource management practices, training and education of a firm's employees should occur before new technologies and innovation are adopted.

2.2 Constrained Shortest Path Problem

Given information regarding level of success (e.g. labor productivity) for all combinations of business practices, respectively, a firm only needs to find the best way to proceed from their current state of operations to the optimal state if managers want the best chance to grow and succeed. If there are only a few organizational practices that may be added or removed from a company's repertoire, then the manager could simply find the best way to move from his or her firm's current state to the optimal state. However, as more options are considered, the complexity of the problem grows exponentially and can no longer be optimized by hand. This is where a mathematical algorithm, specifically a constrained shortest path algorithm (CSPP), becomes ideal in deciding which operational changes should be made in what order and at what times in order to reach the optimal state in the most efficient manner.

CSPP is only NP-complete (in the weak sense) and can be solved through the use of dynamic programming (DP) (Joksch, 1966). Due to the generally high computation time DP emits when implemented in practice, vertex-labeling algorithms based on DP methods have replaced traditional DP procedures (e.g., Aneja et al., 1983; Dumitrescu and Boland, 2003). Other relative improvements to standard DP methods have been developed such as branch and bound via a Lagrangian-based bound (Beasley and Christofides, 1989) and Lagrangian relaxation with *K*-shortest path enumeration (Handler and Zang, 1980).

Carlyle and Wood (2005) have developed an algorithm for enumerating near-shortest paths (NSPs), i.e., all paths that are within ε units of being shortest for a prespecified $\varepsilon \geq 0$. The *NSP algorithm* has been used as a subroutine to solve the *K*-shortest-paths problem supposedly in orders of magnitude faster than previous methods. Consequently, the *Lagrangian relaxation plus enumeration* algorithm (Carlyle et al, 2006), similar to Handler and Zang (1980), requires reevaluations as an alternative procedure for solving CSPP. The use of "near-shortest paths" appears more natural for the Lagrangian Relaxation plus Enumeration for CSPP than implementing "*K*-shortest paths" as used in Handler and Zang (1980). This is due in part to the fact that ordering of paths generally does not add any extra benefit in this context. They also experiment with other techniques, such as preprocessing, to speed up the algorithm.

Dumitrescu and Boland (2003) use a variety of preprocessing procedures along with a vertex-labeling method to form a relatively efficient algorithm for solving the CSPP. In fact, they suggest their technique is the best available at the time. They also implement polynomial-time approximation methods based on this algorithm but with the addition of scaling techniques to speed conversion.

CSPP can be found in numerous applications in the literature, including

- column-generation for generalized set-partitioning models of crew-scheduling/crew-rostering problems (most notably in the airline industry) (Gamache et al., 1999; Vance et al., 1997),
- transportation problems (Nachtigall, 1995; Kaufman and Smith, 1993),
- signal routing for communications networks involving quality-of-service guarantees (Korkmaz and Krunz, 2001),

- the minimum-risk mission planning for military aircrafts/vehicles (Boerman, 1994; Latourell, et al., 1998; Lee, 1995; Zabarankin et al., 2001),
- signal compression (Nygaard et al., 2001), and
- robotics (Suh and Shin, 1988).

This paper appears to add to the literature by applying CSPP to the area of firm-level technology and strategic management decision-making.

3 Research Methodology

3.1 Approaches to the Constrained Shortest Path Problem (CSPP)[11]

The following section will introduce the constrained shortest path problem (CSPP) algorithm intended for this research. Theoretically we could simply use a basic solution approach such as the Bellman-Ford algorithm previously mentioned. However, we would like to make this algorithm as efficient as possible since the problem at hand is NP-complete and large-scale in nature.

Carlyle, Royset and Wood (2006) propose a general approach to solving CSPP for grid networks with singly and multiply constrained CSPPs, including routing military units through road networks. It has been empirically proven to be quite efficient for resource constrained shortest path problems. In the technology management literature there doesn't appear to be any application of this type of algorithm to finding optimal paths from state to state. Most of the literature focuses on finding the optimal state in regards to complementarity and the procedures used to obtain these state values, but there's no mention of determining optimal paths from a firm's current state to its optimal state in an efficient manner.

Research on CSPPs for this problem is important since the process of determining optimal states between a number of operational variables increases in complexity exponentially, which is also the case for CSPPs in general. By determining optimal paths

[11] This section is derived from a variety of sources, namely Ahuja, Magnanti, and Orlin (1993); Aneja, Aggarwal, and Nair (1983); Beasley and Christofides (1989); Benders (1962); Carlyle, Royset, and Wood (2006); Carlyle and Wood, RK, (2005); Dumitrescu and Boland (2003); Fox and Landi (1970); Hadjiconstantinou and Christofides (1999); Handler and Zang (1980); Joksch (1966); Kaufman and Smith (1993); Korkmaz and Krunz (2001).

using simple information (i.e. means) on success measures in a more efficient way using the CSPP approach, results determined through complementarity can be given some verification. This represents a significant gap in the literature and is worth pursuing to make the overall organizational practices adoption process more rigorous. Since we can determine the optimal state and the current state (as well as all of the states in between), trying to efficiently move between the two endpoints is a reasonable pursuit.

We are given a directed network $G = (V,E)$, where V represents a set of vertices (i.e. organizational practices states), and E represents a set of directed edges (u, v) connecting distinct vertices $u, v \in V$. Each edge $(u, v) \in E$ has a length $c_{uv} \geq 0$ (i.e. the cost associated to move from state u to state v) and one or more weights, $f_{iuv} \geq 0$ (representing any other significant factors associated with moving from state u to state v, such as budgetary constraints), for $i \in I$. (Non-negativity of lengths and weights is not an absolute requirement, but this assumption simplifies the following discussion.) Two distinct vertices $s, t \in V$ are defined, as well as a limit $g_i \geq 0$ on path weight (which is specific to a firm, such as its available budget) for each $i \in I$. The *constrained shortest-path problem* (CSPP) is to find a loopless, directed, s-t path p, which we denote here through its edge set $E_p \in E$, such that $\sum_{(u,v)\in E_p} f_{iuv} \leq g_i$ for all $i \in I$ and such that $\sum_{(u,v)\in E_p} c_{uv}$ is minimized.

Let A denote the standard vertex-edge incidence matrix for G, and let $b_s = 1$, $b_t = -1$ and $b_v = 0$ for all $v \in V \setminus \{s, t\}$. Then, CSPP may be written as an integer program (Ahuja et al., 1993, p. 599) called the constrained shortest path integer program (CSPIP):

$$\textbf{CSPIP} \quad z^* = \min_{\mathbf{x}} \mathbf{c}x \tag{1}$$

$$\text{s.t. } A\mathbf{x} = \mathbf{b} \tag{2}$$

$$F\mathbf{x} \leq \mathbf{g} \tag{3}$$

$$\mathbf{x} \geq \mathbf{0}, \ x_{uv} \in \{0,1\}, \tag{4}$$

where equations (3) are the side constraints, and where $x^*_{uv} = 1$ if edge (u, v) is in the optimal path, and $x^*_{uv} = 0$, otherwise. Also note that the problem's structure leads to binary solutions without explicit constraints $\mathbf{x} \leq \mathbf{1}$.

When the side constraints, $F\mathbf{x} \leq \mathbf{g}$, are ignored, this problem is a standard shortest path problem and can be solved easily. However, when including the constraints, the CSPIP algorithm is generally inefficient to solve. In most applications there are a relatively small number of these constraints, thus relaxing them is a reasonable method to begin the optimization algorithm. Using Lagrangian relaxation, it can be shown that for any row vector $\boldsymbol{\lambda} \geq \mathbf{0}$,

$$z^* \geq \underline{z}(\boldsymbol{\lambda}) = \min_{\mathbf{x}} \mathbf{c}x + \boldsymbol{\lambda}(F\mathbf{x} - \mathbf{g}) \tag{5}$$

$$\text{s.t. } A\mathbf{x} = \mathbf{b} \tag{6}$$

$$\mathbf{x} \geq \mathbf{0}, \ x_{uv} \in \{0,1\}, \tag{7}$$

From here we can rewrite the objective function and optimize the Lagrangian lower bound z^* through the construction of the following constrained shortest path Lagrangian relaxation problem (CSPLR):

$$\textbf{CSPLR} \quad z^* = \max_{\lambda \geq 0} \ \underline{z}(\boldsymbol{\lambda}) \tag{8}$$

$$= \max_{\lambda \geq 0} \ \min_{\mathbf{x}} (\mathbf{c} + \boldsymbol{\lambda}F)\mathbf{x} - \boldsymbol{\lambda}\mathbf{g} \tag{9}$$

$$\text{s.t. } A\mathbf{x} = \mathbf{b} \tag{10}$$

$$\mathbf{x} \geq \mathbf{0},\ x_{uv} \in \{0,1\}, \tag{11}$$

Computing $\underline{z}(\boldsymbol{\lambda})$, given a fixed $\boldsymbol{\lambda} \geq 0$, involves finding the solution of the shortest-path problem with Lagrangian-modified edge lengths. The outer maximization of $\boldsymbol{\lambda}$ can be solved in many ways, depending on the number of side constraints in the problem. The solution methods include

- bisection search for one side constraint (Fox and Landi, 1970),
- coordinate search for a few side constraints (e.g., DeWolfe, Stevens and Wood, 1993),
- through a linear-programming master problem as in Benders decomposition (Benders, 1962), or
- subgradient optimization (Beasley and Christofides, 1989).

A simple and commonly used implementation of finding an appropriate value of $\boldsymbol{\lambda}$ through subgradient optimization (based on the aforementioned authors) is shown next.

Suppose $L(\boldsymbol{\lambda}) = \min \{cx + \boldsymbol{\lambda}\,(Fx - g) : Ax = b,\ x \in X\}$ has a unique solution x' and is differentiable. Then the solution x' remains optimal for small change of $\boldsymbol{\lambda}$ (i.e. $\boldsymbol{\lambda} \leftarrow \boldsymbol{\lambda} + \theta\,(Fx' - g)$). So $(Fx' - g)$ represents the direction and θ represents the step size. The intuitive interpretation is as follows:

- When $(Fx' - g)_i = 0$, the solution x' uses up exactly the required units of the ith resource, we hold $\boldsymbol{\lambda}_i$.
- When $(Fx' - g)_i < 0$, the solution x' uses up less than the available units of the ith resource, we decrease $\boldsymbol{\lambda}_i$.

– When $(Fx' - g)_i > 0$, the solution x' uses up more than the available units of the ith resource, we increase λ_i.

For Lagrangian multiplier updating, we define the following variables:

– $\lambda^{k+1} \leftarrow max\{\lambda^k + \theta_k (Fx^k - g), 0\}$

– λ^0 : any initial choice of the Lagrangian multiplier

– x^k : any solution to the Lagrangian subproblem when $\lambda = \lambda^k$

– θ_k : step length at the kth iteration

The choice of the step sizes θ_k are important for convergence to an optimal solution of the multiplier problem. The condition for convergence is $\theta_k \to 0$ and $\sum_{j=1}^{k} \theta_j \to \infty$. One simple example is just to set $\theta_k = \frac{1}{k}$. However, by using an adaptation of Newton's Method, we can come up with a more logical step size. First let $L(\lambda^k) = cx^k + \lambda^k (Fx^k - g)$ where x^k solves Lagrangian subproblem when $\lambda = \lambda^k$ and $L(\lambda) \approx r(\lambda) = cx^k + \lambda (Fx^k - g)$ be the linear approximation. Then suppose we know the optimum value L* of the Lagrangian multiplier problem. Then

$r(\lambda^{k+1}) = cx^k + \lambda^{k+1} (Fx^k - g) = L^*$ and $\lambda^{k+1} \leftarrow \lambda^k + \theta_k (Fx^k - g)$

➔ $r(\lambda^{k+1}) = cx^k + [\lambda^k + \theta_k (Fx^k - g)] (Fx^k - g) = L^*$

➔ $$\theta_k = \frac{L^* - L(\lambda^k)}{\left\| Fx^k - g \right\|^2}.$$

However, we don't know the objective function value of L^* for the Lagrangian multiplier problem. A reasonable and popular heuristic for selecting the step length is

$\theta_k = \dfrac{\mu^{k^*}\left[UB - L(\lambda^k)\right]}{\left\|Fx^k - g\right\|^2}$, where UB is the upper bound on the optimal objective function z^* of the problem (CSPIP) and μ^k is a scalar chosen (strictly) between 0 and 2. One can start with $\mu^k = 2$ and then reduce μ^k by a factor of 2 until failing to find a better solution.

Because $F\mathbf{x} \le \mathbf{g}$ is an inequality constraint, the update formula $\boldsymbol{\lambda}^{k+1} \leftarrow \boldsymbol{\lambda}^k + \theta_k (Fx^k - g)$ might cause λ to become negative. To avoid this possibility, $\boldsymbol{\lambda}^{k+1} \leftarrow max[\boldsymbol{\lambda}^k + \theta_k (Fx^k - g), 0]$. The full subgradient optimization method optimizing for obtaining a lower bound $\underline{z}(\lambda)$ is shown in Figure 4.

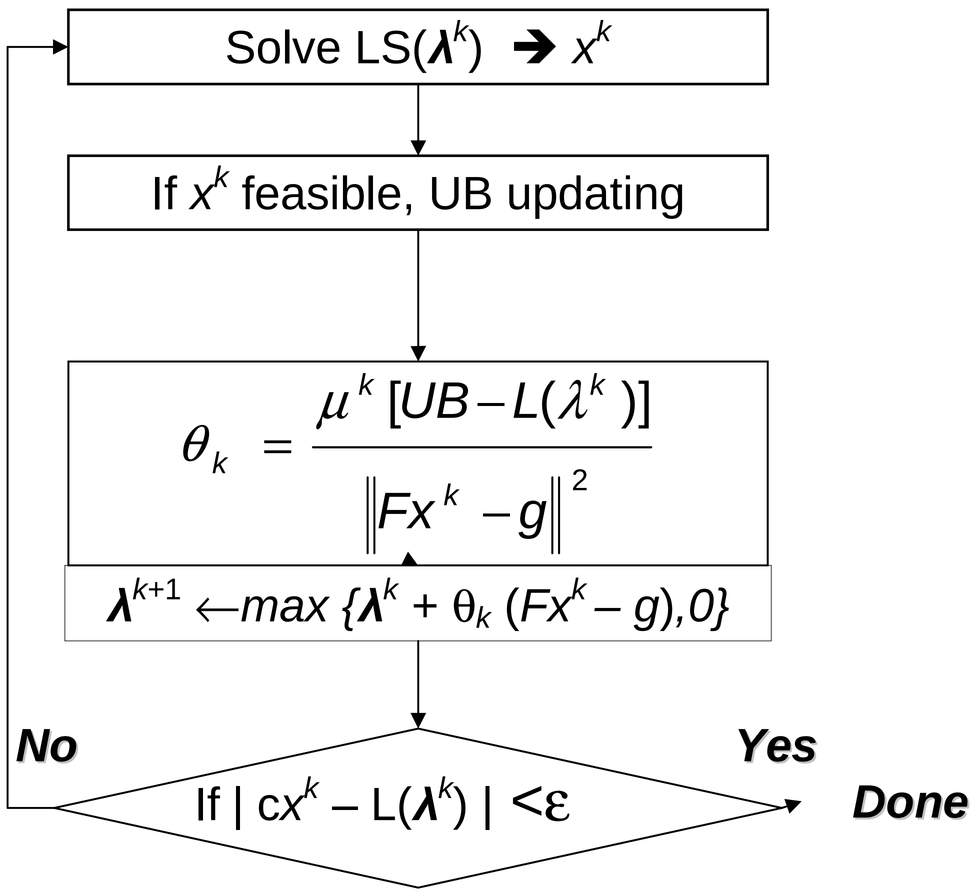

Figure 4. Subgradient Optimization Method (LS(λ): Lagrangian Subproblem at λ =λ)

Often times one finds a solution $\hat{\mathbf{x}}$ that is feasible in terms of the relaxed weight constraints (3) (in addition to constraints (2) and (4)) while optimizing $\underline{z}(\boldsymbol{\lambda})$. Specifically, if F is a non-negative matrix, by making the vector $\boldsymbol{\lambda}$ sufficiently large, violation of the constraints $F\mathbf{x} \leq \mathbf{g}$ is discouraged, and a feasible solution typically results. We will assume we have found a feasible solution $\hat{\mathbf{x}}$, and can therefore compute the upper bound $\bar{z} \equiv \mathbf{c}\hat{\mathbf{x}} \geq z^*$.

If we have a an upper bound, $\bar{z}$, and an apparently "good" (at least near-optimal) vector $\boldsymbol{\lambda}$, the problem of solving for $\mathbf{x}^*$ may be seen as one of straightforward enumeration:

Theorem 1 (implied from Handler and Zang, 1980; stated by Carlyle, Royset, and Wood , 2006) *Let $\hat{X}(\lambda, \bar{z})$ denote the set of feasible solutions to* **CSPLR** *such that $\mathbf{c}\hat{\mathbf{x}} + \lambda(F\hat{\mathbf{x}} - \mathbf{g}) \leq \bar{z}$. Then, $\mathbf{x}^* \in \hat{X}(\lambda, \bar{z})$. That is, an optimal solution $\mathbf{x}^*$ to* **CSPIP** *can be identified by enumerating $\hat{X}(\lambda, \bar{z})$ and selecting*

$$x^* \in \underset{\mathbf{x}\in\hat{X}(\lambda,\bar{z})}{\arg\min}\, \mathbf{cx} \qquad (12)$$

Since $F\mathbf{x}^* \leq \mathbf{g}$ and $\boldsymbol{\lambda} \geq \mathbf{0}$, the theorem follows from the facts that

(i) $\mathbf{c}\mathbf{x}^* + \lambda(F\mathbf{x}^* - \mathbf{g}) \leq z^*$, and

(ii) $z^* \leq \bar{z}$.

If we would like to exponentially reduce the size of $\hat{X}(\lambda, \bar{z})$ and thereby exponentially reduce computational workload, we need to use an optimal (or near-optimal) λ for CSPLR. However, in order to satisfy Theorem 1 and thus solve CSPIP, only a $\boldsymbol{\lambda} \geq \mathbf{0}$ is required.

Note that Theorem 1 implies that complete enumeration (enumeration of each path, represented here by $\hat{\mathbf{x}}$) may be required where $(\mathbf{c}+\lambda F)\hat{\mathbf{x}} - \lambda\mathbf{g} \leq \bar{z}$. In other words, if $\mathbf{x}^*{}_\lambda$ solves the shortest path problem given the edge-length vector $\mathbf{c}+\lambda F$, and $\underline{z}(\lambda) \equiv (\mathbf{c}+\lambda F)\hat{\mathbf{x}}^*{}_\lambda - \lambda\mathbf{g}$ then CSPP is solved by enumerating all paths $\hat{\mathbf{x}}$ such that $\underline{z}(\lambda) \leq (\mathbf{c} + \lambda F)\hat{\mathbf{x}} - \lambda\mathbf{g} \leq \bar{z}$[12]. In turn, this means that, given edge-length vector $\mathbf{c} + \lambda F$, we can identify all the ε-optimal paths for $\varepsilon \equiv \bar{z} - \underline{z}(\lambda)$. In this setting, an NSP algorithm appears to be a more logical choice for purposes of enumeration than a *K*-shortest-paths (KSP) algorithm, which is designed to enumerate the *K* shortest paths for an integer *K* chosen beforehand. Relatively efficient KSP algorithms (e.g., Hadjiconstantinou and Christofides, 1999) can and have been used. These algorithms also appear to be a reasonable choice since they enumerate paths in order of increasing length, and can be stopped when the path length exceeds the definition of near-optimal as definite by $(\mathbf{c} + \lambda F)\mathbf{x}^*{}_\lambda + \varepsilon$. This length-ordering enumeration uses extra computational work and complexity, whereas the NSP algorithm of Carlyle and Wood (2005) is intuitively and practically much more efficient.

3.2 Lagrangian Relaxation and Enumeration Algorithm for CSPP

We can now describe the basic Lagrangian Relaxation Enumeration approach for solving the CSPP.

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[12] The inequality $\underline{z}(\lambda) \leq (\mathbf{c} + \lambda F)\hat{\mathbf{x}}$ always holds since by definition $\underline{z}(\lambda)$ is equal to the length of the shortest path $\mathbf{x}^*{}_\lambda$ with respect to the Langrangianized edge lengths $\mathbf{c} + \lambda F$.

Lagrangian Relaxation Enumeration Algorithm for CSPP[13]

1. Reformulate the original constrained shortest path integer program (CSPIP) into a constrained shortest path Lagrangian relaxation (CSPLR) problem.
2. Use subgradient optimization to optimize the Lagrangian lower bound ($\underline{z}(\boldsymbol{\lambda})$) to find an optimal or near-optimal Lagrange multiplier vector $\boldsymbol{\lambda}$.
3. If a feasible path $\hat{\mathbf{x}}$ was found during the subgradient optimization procedure, then let $\bar{z} \equiv \mathbf{c}\hat{\mathbf{x}} \geq z^*$ be the upper bound on z^*. If a feasible path was not found, set $\bar{z} = (|V|-1)\max_{e\in E} c_e$.
4. Begin the Near Shortest Path (NSP) algorithm (Carlyle and Wood, 2005) that enumerates all paths $\hat{\mathbf{x}}$ such that $(\mathbf{c} + \boldsymbol{\lambda}F)\hat{\mathbf{x}} - \boldsymbol{\lambda}\mathbf{g} \leq \bar{z}$, by first computing
    - the minimum "Lagrangian distance" $d(v)$ from each $v \in V$ back to t by solving a single, backwards, shortest-path problem starting from t using Lagrangianized edge lengths $\mathbf{c}(\boldsymbol{\lambda}) = \mathbf{c} + \boldsymbol{\lambda}F$,
    - the corresponding minimum distances from v to t for each $v \in V$ with respect to original edge lengths $\mathbf{c}$, and
    - the corresponding minimum distances $d_i(v)$ from v to t for each $v \in V$ and $i \in I$ with respect to edge weights f_i.

[13] See Appendix A for the associated Matlab code created for this dissertation; basic algorithm developed by Carlyle, Royset, and Wood , 2006.

A standard path-enumeration algorithm (e.g. Byers and Waterman (1984)) is then begun from s, where the current s-u subpath is extended along an edge (u, v) if and only if

- the length of the current subpath, denoted $l(u)$, plus $c_{uv}(\lambda)$, plus $d'(v)$, does not exceed the definition of "near-shortest", and
- the path does not loop back on itself.

In addition, use the side constraints to reduce the amount of enumeration by not extending the current s-u subpath along an edge (u, v) that would further lead to a violation of any of the side constraints. Also, if the length of that path, with respect to true edge lengths **c**, cannot be shorter than $\bar{z}$ when extending the subpath along (u, v), do not extend the subpath. In other words, do not extend a subpath when it would lead to violation of the inequality, $\mathbf{cx} \le \bar{z}$.

Then update the current solution, $\hat{\mathbf{x}}$, and the upper bound, $\bar{z} = \mathbf{c}\hat{\mathbf{x}}$, whenever a better solution is detected.

5. The best solution, $\hat{\mathbf{x}}$, discovered during this process, is optimal.

Since the path-enumeration component of the algorithm does not recalculate distances $d'(w)$, $\forall\, w \in V$, after adding an edge to the current subpath, it may require exponential work per path. An implementation that recalculates these values described by paths that do not intersect the current subpath (and so can change as the algorithm proceeds) is theoretically more efficient. Although this method does not recalculate these values $d'(w)$ ($\forall\, w \in V$), the values that are used in the algorithm are lower bounds on the on the theoretical values. These approximate values still lead to correct solutions. Moreover, this method has been empirically shown to be the more efficient than the theoretically efficient method (Carlyle and Wood, 2005).

As with many methods of optimization, this algorithm can easily be modified to become an approximation algorithm in which it finds a near-optimal solution (a solution within δ units of optimality, where $\delta > 0$), if desired. This generally leads to less computational power required for a solution.

The LRE method essentially incorporates a branch-and-bound procedure where it branches by extending the current subpath by one edge. It does this branching by using a depth-first enumeration tree while also checking feasibility along the way. If we were to use a linear programming branch-and-bound technique, the Lagrangian lower bound ($\underline{z}(\lambda)$) would need to be reoptimized each time an edge was added. This would mean more shortest paths would need to be found and would result in a significant extra amount of computation. How it currently stands, LRE updates the bound but does not reoptimize it.

3.3 CSPP Improvements and Extensions

Refinements of the Lagrangian Relaxation Enumeration algorithm implement preprocessing to remove sections of the graph that cannot form part of an optimal solution. One such example is if we solve a shortest-path problem from *s* and solving another shortest-path problem backward from *t* (for all edge weights, respectively and for all vertices), then we can possibly eliminate vertices and edges that if included in a solution would violate one more of the side constraints. This kind of preprocessing doesn't generally improve the computation time for this method as much as it would for a vertex-labeling algorithm since the enumeration technique already skips searching parts of the graph that result in violation of the constraints. The algorithm also skips searching parts of the graph whose inclusion would lead to a worse solution than the current best. It is worth noting that since these preprocessing techniques require relatively low overhead, they can still give some improvement to the algorithm (Beasley and Chroistofides, 1989; Carlyle, Royset and Woods, 2006).

Another refinement technique which may have a significant effect on the solution time is to eliminate redundant constraints from the original LP-formulation. For this, a *hit-and-run* (Berbee et al., 1987) or *stand-and-hit* (Caron, Boneh, and Boneh, 1997) Monte Carlo method could be ran in the preprocessing stage in order to detect most or all necessary constraints in the problem, and thus remove some or all unnecessary constraints. These methods would prove most significantly useful for problems with a large number of side constraints, especially when a vast majority of those constraints are redundant. This method would also aid in reducing the amount of preprocessing from the previous refinement mentioned.

One more significant refinement in this algorithm that would be very useful is one that deals with infeasibility. More specifically, if there is no solution to the shortest *s*-*t* path as a result of one or more side constraints being violated, then it would be preferable to search for the shortest path from the source, *s*, to the second-best sink node, *t'*. The simplest way to do this is to run the whole algorithm over using *s* and *t'* as the new nodes of choice. However, using information from the last iteration of the algorithm should be a more efficient method to accomplish this.

It may also be the case that for some large-scale problems, the time the algorithm uses to reach optimality may be too long and thus a time/optimality trade-off rule may be considered to ensure a "reasonable" solution is reached. Other refinement opportunities are sure to exist as well.

So far we have only discussed using mean values of success measures of a firm to determine which state(s) is (are) optimal. Using robust optimization would be helpful in cases for risk-averse managers. Under robust optimization, the optimal solution is determined under the worst-case scenarios. This can easily be implemented into the research by:

- using the minimum values found for success (e.g. profit) or
- approximating the distribution function of the measures and picking a value at the low end of the distribution.

An alternative to using a robust optimization technique is stochastic optimization. Using stochastic optimization, distribution functions can be constructed for each state in terms of the associated success measure. Then a random value can be generated for each state and the LRE algorithm can be ran. This process would be repeated several times and the results analyzed to determine the frequency of paths chosen through each run of the LRE algorithm. The major drawback of this technique is that the LRE algorithm would need to be ran multiple times which adds much more computational time. Thus the stochastic optimization method would be more suited for smaller-sized problems where efficiency is of less concern.

A logical extension to LRE could be to allow multi-period planning where there could be a separate set of constraints for each period. For long-range planning, it is realistic to assume that budget constraints and organizational practice adoption costs could change as time passes. Given the dataset previously mentioned, this method may be implemented by managers that are interested in a more thorough organizational analysis of their firm and who are not worried about the extra computational work required to obtain it.

3.4 Methods Implemented and Developed for the Thesis

In this paper, two of the leading algorithms for solving CSPP's are implemented in Matlab and tested against a method developed by this author. A general description of each of these methods follows.

3.4.1 D&W Method (Dumitrescu & Boland, 2003)

Dumitrescu and Boland (2003) (whose method is sometimes referred to as the D&B algorithm in this thesis) found that their label-setting method which makes full use of information found in preprocessing was the best method (under empirical analysis) at the time in terms of both time and memory compared to implementing other methods, including those using Lagrangean relaxation techniques. Although they present the algorithm and their empirical analyses for solving problems involving only one weight constraint, the algorithm can easily be extended to multiply-constrained problems.

The technique used for the label-setting algorithm (LSA) is based off of Desrochers and Soumis (1988). The LSA uses a set of *labels* for each node. Each label on a node represents a different path from node *s* to that node and consists of a pair of numbers representing the cost and the weight (which could consists of an array of numbers for multiple weights) of the corresponding path. The algorithm finds efficient labels on every node. No labels having the same cost are stored, and for each label on a node, any other node with lower cost must have a greater weight. Starting only with the label $(0,\vec{0})$ on node *s*, the algorithm extends the set of all labels by *treating* an existing label on a node, that is, by extending the corresponding path along all outgoing arcs. At each step, the untreated label with least weight is treated.

To further illustrate the LSA method, they describe terms for node labels that are dominating and efficient, respectively. A label corresponding to a given node represents a path from the start node *s* to the current node *i*. This is represented by the side-constraints' weights on the path as well as the total cost of the path. A label corresponding to node *i* dominates another label of node *i* if its side constraint weights and costs are all less than or equal to the other label's weights and cost, respectively. A label is considered efficient if it not dominated by another label at node *i*.

First, the algorithm performs preprocessing on all nodes except the end node, *t*. This involves considering least weighted paths from the start node to each node in the graph and from each node in the graph to the end node (e.g. maximum state), for each side constraint weight. This requires two shortest path calculations for each weight restriction as well as for the costs data. Any node or arc which cannot be used to complete a path from the start to the end node without violating a side constraint weight limit can be deleted from the graph. This was first described by Aneja et al (1983). However, Dumitrescu and Boland's method was unique in that their algorithm continues to update the upper bound on costs whenever the graph was reduced.

During label treatments, D&B eliminate labels corresponding to feasible partial paths that cannot be extended to feasible paths to *t*. D&B also ignore a new label created at a node can even if it is not dominated by any of the labels already existing at that node, if it cannot produce a *better* solution than one already found. The algorithm also updates the upper bound during the whenever a better one is found. If the path corresponding to the new label is extended by the path of minimum cost from the current node to *t* and the result is weight feasible and has cost smaller than the upper bound, then the upper bound is updated.

They do not use *strict* inequality when deciding whether nodes or arcs should be deleted from the graph, so the optimal path might have been destroyed in preprocessing. In this case the optimal path is the one that yielded the upper bound found in preprocessing. As a result, if the path that is outputted by the label-setting algorithm has cost greater than the upper bound obtained in preprocessing or if node *t* remains unlabeled at the conclusion of the algorithm, then the optimal solution is the least cost feasible path obtained in preprocessing.

3.4.2 CRW Method (Carlyle, Royset, & Wood, 2006)

This method follows the basic structure shown in section 3.2, i.e. the Lagrangian relaxation and enumeration approach with some subtle differences. First, they use a bisection search method (Fox and Landi, 1970) for solving the outer maximization over $\boldsymbol{\lambda}$. This technique has been shown to work well for a relatively small number of side constraints, but not for a large number of constraints.

The CRW method also incorporates preprocessing (analogous to the one used by the D&B method) so as to reduce the network and thus computational load of the main

LRE algorithm. Preprocessing may also aid in finding a tighter Lagrangian bound. The preprocessing method starts by computing the minimum-weight subpath from the start node *s*, to every node in the graph, and the minimum weight subpath from every node in the graph to the end node, *t*, for each corresponding side constraint weight. Then the algorithm deletes any edge that can't be further connected to *s* and *t* without violating one of the side constraints. Then the preprocessing method can be continually repeated until no further edges can be deleted. It should be noted that while edges are being deleted, nodes may be removed as well as a consequence.

How the LRE algorithm is set up, it checks to see if an edge is added to the current subpath, can the subpath be further extended to *t*, so that the cost constraint doesn't exceed the current upper bound, the Lagrangianized weight constraint doesn't exceed the upper bound, and the individual weight constraints don't exceed their given bounds, respectively. It is possible that each of these constraints may be satisfied, but by extending the subpath along a different route to *t*, but no one extension that satisfies all of the constraints. The CRW method tries to improve this gap in the LRE algorithm by aggregating the three kinds of constraints. They do so by combining subsets of the constraints as well as combining all of them into a single constraint. This translates into creating more side constraints for each of these sets of combinations. Although creating more computational overhead, they believe the time saved through reduction of the solution space outweighs the extra computational effort involved.

Recall in step 3 of the LRE algorithm, if a feasible path is not found, then $\bar{z} = (|V|-1)\max_{e\in E} c_e$, which can lead to a substantially large number of enumerations than if a tighter bound is discovered and used in the rest of the algorithm. The CRW method attempts to improve this bound (for problems involving more than one side constraint), but replacing the objective function with one of the side constraints, thus removing the restriction, g_i, for that side constraint. The LRE algorithm is ran on the reduced problem, but does not need to solve to optimality. Instead the LRE algorithm is terminated when a feasible solution is identified that does not violate the side constraint restriction that was previously relaxed. Once this feasible solution is found, the upper bound may be set and the original LRE problem may be solved to optimality.

3.4.3 CSPP Method (Developed for this Thesis)

The CSPP algorithm is similar to the CRW method in that it uses the same structure as the LRE method, uses some of the ideas from the CRW modifications, but with additional modifications of its own. One difference is the CSPP method uses subgradient optimization instead of bisection search as in the CRW method. This method is generally regarded as a reasonable method to use when solving large problems with many weight restrictions.

The CRW method never performs re-optimization of the Lagrangian lower bound after extending subpaths during the LRE method, hypothesizing that the extra computation would not be worthwhile. The CSPP method reoptimizes the lower bound periodically in the early enumerations of the algorithm (when the optimality gap is generally greater), and halts when lower improvements are sufficiently small. This method appears to work well in practice.

As mentioned in the previous section (3.4.2), the CRW method uses aggregated bounds to create additional checks of feasibility in the algorithm. They do this using five additional tests, one for aggregating all weights into one single weight, then combining every pair of the aggregated weight, cost, and Lagrangian lengths (three tests), and then by combining all three. A further extension is created in CSPP to further subdivide the aggregated weight further instead of just considering all weights combined at once. For problems involving two or more side constraints, two aggregated weight constraints were arbitrarily assigned instead of one to see if further improvements could be made to the algorithm and the results were generally in favor of doing so. Further work could be examined regarding this technique to determine how many subgroups of weight constraints should be created to optimize the algorithm.

In addition to these modifications mentioned, preprocessing similar to that used in the D&W and CRW methods are implemented in CSPP, as well as the method of tightening up the upper bound in cases where feasible path(s) are not found during step 2 of the LRE algorithm. They were both found to be useful enhancements to the algorithm.

3.5 An Illustrative Example

An example was run on a simple problem involving two practices and thus four possible states of adoption for those practices. We may use binary algebra to represent the states. Let state 0 (00 in binary algebra) represent no practices adopted, state 1 (01) represent only the second practice being adopted, state 2 (10) as only the first practice adopted, and state 3 (11) as both practices being adopted. The cost vector for this problem is simply $c = \begin{bmatrix} \overset{01}{1} & \overset{02}{1} & \overset{10}{1} & \overset{13}{1} & \overset{20}{1} & \overset{23}{1} & \overset{31}{1} & \overset{32}{1} \end{bmatrix}$ since each adoption or rejection of a practice results in a change chosen by the firm and we want to minimise the amount of changes implemented to get from the current state to the optimal state.

It should also be noted that in this research, only single changes, i.e. either adding one practice or removing one practice, are allowed at one time (from state to state). Thus, there are no edges in the graph that connect representations for changing more than one practice at a time. For example, a firm is not allowed to move from state 0 (not implementing either practice) to state 3 (implementing both practices). This restriction was implemented in the research primarily to aid in creating solution sets involving more state traversals to the maximum attainable states, thus creating more complex solution sets. The algorithm (and Matlab program) allows for complete graphs to be inputted and solved to optimality, if desired.

Let's assume that the profit margin (the measure of success used for this particular problem) for each state of practice adoption can be represented by the vector $\begin{bmatrix} \overset{0}{4} & \overset{1}{9} & \overset{2}{7} & \overset{3}{12} \end{bmatrix}$. Let's also assume that we start in state 0 (no practices currently adopted) and the optimal state is state 3 (both practices are adopted). This means that implementing both practices results in the highest profit margin for the firm. Then

$$A = \begin{array}{c} \\ 0 \\ 1 \\ 2 \\ 3 \end{array} \begin{array}{c} \begin{array}{cccccccc} 01 & 02 & 10 & 13 & 20 & 23 & 31 & 32 \end{array} \\ \begin{bmatrix} 1 & 1 & -1 & 0 & -1 & 0 & 0 & 0 \\ -1 & 0 & 1 & 1 & 0 & 0 & -1 & 0 \\ 0 & -1 & 0 & 0 & 1 & 1 & 0 & -1 \\ 0 & 0 & 0 & -1 & 0 & -1 & 1 & 1 \end{bmatrix} \end{array}$$

denotes the standard vertex-edge incidence matrix for G, and $b_0 = 1$, $b_3 = -1$ and $b_v = 0$ for all $v \in V \backslash \{0,3\}$. Let the resource constraint matrix, F = $\begin{bmatrix} \overset{01}{9} & \overset{02}{4} & \overset{10}{5} & \overset{13}{10} & \overset{20}{2} & \overset{23}{3} & \overset{31}{5} & \overset{32}{7} \end{bmatrix}$ and limiting path weight $g = 10$. An example of a resource constraint would typically be that of a budget. Thus g could represent how much money the manufacturing firm has available to spend on practice adoption (in thousands of dollars). F then represents how much money it would cost to move from one state of practices to another state (again in thousands of dollars). So to move from implementing the first practice (state 2) to implementing both practices (state 3) costs $3,000. The constrained shortest path integer program is as follows:

$$\textbf{CSPIP} \quad z^* = \min_{\mathbf{x}} \mathbf{c}x \tag{1}$$

$$\text{s.t. } A\mathbf{x} = \mathbf{b} \tag{2}$$

$$F\mathbf{x} \le \mathbf{g} \tag{3}$$

$$\mathbf{x} \ge \mathbf{0} \text{ and integer,} \tag{4}$$

It can easily be seen (by inspection) that the optimal solution is the chain of state transitions 0 → 2 → 3. The chain represents moving from having no practices adopted (00) to adopting the first practice (10) to adopting both practices (11). This results in the least-cost practices adoption path to the most profitable state of adoption. This path of implementation, as seen in Figure 5, leads the firm to its optimal state in the least amount of organizational changes and does so using 7 resource units, which is less than the 10 units allotted. If we had chosen to adopt the second practice and then the first, this would have led to using 19 resource units, which would have violated our resource constraint $g = 10$.

Again, we can note that Figure 5 is not a complete graph due to the assumptions that firms can only make a single organizational change at a time. For example, there does not exist an arc from state 1 to state 2 because this would involve removing one organizational practice while simultaneously adding the other practice. We could add more arcs to create a complete graph, however, the single practice changes are prohibited in the models presented in the research in order to reduce the occurrences of trivial solutions arising. We want to avoid frequent optimal solutions consisting of state transition (e.g. 0 → 3).

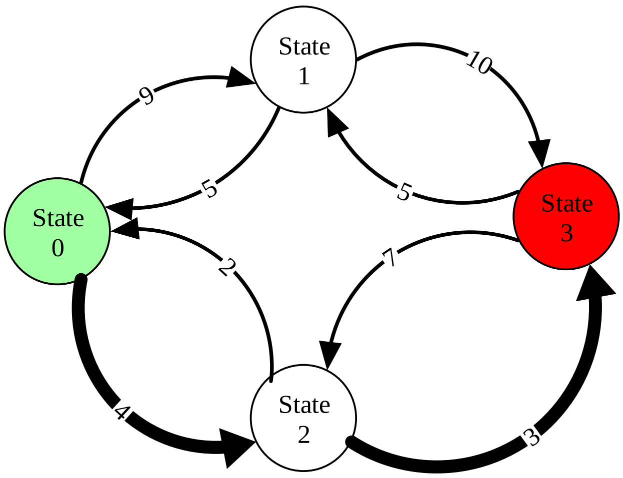

Figure 5. Optimal path from State 0 (no organizational practices) to State 3 (both practices) shown in bolded arcs resource constraint values represented on the arcs

By inputting the data into the LRE method described in section 3.2 (also see Matlab code in Appendix A), the optimal solution was as expected and was performed in nearly zero seconds as was expected for such a small problem. However, for each increase in organizational practices considered in the problem, the number of states increases exponentially. In fact the number of states in the CSPP problem is 2^n, where *n* is the number of technology and/or business practices considered. Also, as the number of constraints (such as resource constraints) increases, the complexity of the problem increases as well.

The above problem is a simple example to illustrate the idea. To illustrate how problem complexity increases with just two additional technologies, see Appendix D. A more typical problem involves considering a much larger set of possible organizational changes, say 40 in total. This would result in 2^{40} = 1,099,511,627,776 states of nature.

Obviously this problem can't be easily illustrated. The number of constraints could widely vary depending on how tightly managed a specific firm is. The more tightly constrained a firm is in regards to its decisions and resources, the more constraints there will be in the coinciding CSPP problem. For a more complex example of the CSPP algorithm, see Appendix D.

3.6 Remarks

The best method to solve the proposed organizational practices problem depends on the case at hand. As previously stated, a relatively small case could easily be solved by a simple and generally inefficient method. However, the more interesting problems are those that are considerably larger and more complex. Since the CSPP problem is NP-complete, any improvement in efficiency to the existing algorithms is worthwhile in order to solve large-scale problems in a shorter and more reasonable amount of time. This will result in saving managers time and money. Most problems managers care about are the ones that are very large and complex, so making these problems easier to solve is a worthwhile pursuit.

It can't be guaranteed which algorithm will work 'best' for all problem sets. Each method can outperform the other for specific problem types and sizes. A wide array of test cases will be ran using the algorithms to determine efficiency and compare the results to alternative leading methods in the literature. The goal is to see how this algorithm performs in relation to alternative methods, using both a real-world data set as well as randomly generated data.

4 Preliminary Analysis

4.1 Data

Using the CSPP algorithm developed in section 3, we wanted to perform empirical analysis in regards to technology and strategic management decision-making in Canada. In this chapter we describe the data set used, the sampling performed, and the set of organizational practices examined in the empirical work performed in section 5.2.

4.1.1 Description[14]

The dataset used in this paper is Statistics Canada's Workplace and Employee Survey (WES), which was created to explore a broad range of issues relating to employers and their employees. The survey aims to shed light on the relationships among competitiveness, innovation, technology use and human resource management on the employer side, and technology use, training, job stability and earnings on the employee side.

The survey was/is conducted annually since 1999 and to this date, data releases include 1999 through 2004. The survey is unique in that employers and employees are linked at the micro data level. Employees are selected from within sampled workplaces. Thus, information from both the supply and demand sides of the labor market is available. The Workplace and Employee Survey offers potential users several unique innovations: chief among these is the link between events occurring in workplaces and the outcomes for workers. In addition, being longitudinal (i.e. collecting data from the

[14] For the complete list of all the survey variables used in this analysis, see Appendix C.

same individual firms over several years), it allows for a clearer understanding of changes over time.

The target population for the employer component is defined as all business locations operating in Canada that have paid employees in March, with the following exceptions:

a) Employers in Yukon, Nunavut and Northwest Territories; and
b) Employers operating in crop production and animal production; fishing, hunting and trapping; private households, religious organizations and public administration.

The target population for the employee component is all employees working or on paid leave in March in the selected workplaces who receive a Canada Revenue Agency T-4 Supplementary form. If a person receives a T-4 slip from two different workplaces, then the person will be counted as two employees on the WES frame.

4.1.2 Sampling

This data set is a sample survey with a longitudinal design. There are two reference periods used for the WES. Questions concerning employment breakdown use the last pay period of March for the reference year while other questions refer to the last 12-month period ending in March of the reference year. The survey frame of the "Workplace" (employer) component of WES is created from the information available on the Statistics Canada Business Register.

Prior to sample selection, the business locations on the frame are stratified into relatively homogeneous groups (i.e. strata), which are then used for sample allocation and selection. The WES frame is stratified by industry (14), region (6), and size (3), which is defined using estimated employment. The size stratum boundaries are typically different for each industry/region combination. The cut-off points defining a particular size stratum are computed using a model-based approach. In 1999, 9,043 business locations were selected. In 2001, 1,792 locations were added for a total of 10,815. In 2003, 2,334 locations were added for a total of 13,149 business locations.

The survey frame of the Employee component of WES is based on lists of employees made available to interviewers by the selected workplaces. A maximum of twenty four employees are sampled using a probability mechanism. In workplaces with fewer than four employees, all employees are selected. Employees are followed for two years only, due to the difficulty of integrating new employers into the location sample as workers change companies. As such, fresh samples of employees are drawn on every second survey occasion (i.e. first, third, fifth).

Below in Table 1 are the sample sizes (number of respondents) for each of the 6 years of WES.

	Sample Sizes (number of respondents)	
Year	**Workplace**	**Employee**
1999	6,322	23,540
2000	6,068	20,167
2001	6,207	20,352
2002	5,818	16,813
2003	6,565	20,834
2004	6,159	16,804

Table 1. Sample sizes (number of respondents) from the Workplace and Employee surveys from WES (1999 - 2004)

For the linked Workplace/Employee datasets, the sample size was over 35,000 respondents for the growth variables. The linkage here refers to combining the workplace responses with each of the associated employees who respond to the employee survey. The sample size could have been much larger except that some workplaces do not participate each year due to factors such as bankruptcy, merger, or acquisition, for example.

The dataset of workplaces is divided into 14 specific industries, labelled 01 through 14 as shown in Table 2:

Class Number	**Industry**
01	Forestry, mining, oil, and gas extraction
02	Labor intensive tertiary manufacturing
03	Primary product manufacturing
04	Secondary product manufacturing
05	Capital intensive tertiary manufacturing
06	Construction
07	Transportation, warehousing, wholesale
08	Communication and other utilities
09	Retail trade and consumer services
10	Finance and insurance
11	Real estate, rental and leasing operations
12	Business services
13	Education and health services
14	Information and cultural industries

Table 2. Industry classification numbers and descriptions for the WES survey set

Having six years of economic data (1999 through 2004) allows for the construction of growth in labor productivity and in profit (price-cost margin). This results in five growth periods (1999-2000 through 2003-2004). From the dataset we found the means and standard deviations of profit and labor productivity. The means were used to determine what states are optimal and standard deviations help to determine which states are significantly different from others in terms of performance.

Next, resource constraints were constructed in terms of technology (hardware/software or other) costs associated with maintaining or implementing technology. This was needed in the event that a given workplace had a financial constraint on their operational expenditures. Other resource constraints that could be included in the optimization model that are specific to a given workplace such as their overall budget as well as any policies they need to adhere to, can easily be added to the model. For generality of the model these will not be the focus of this research.

4.1.3 Management States and Associated Variables (Employee Survey)

1 Training

Employees were asked if in the past year, they received any of the training mentioned in Table 3:

Variable Name	Type of Training
CLASSTRAIN:	Formal Training (In The Classroom)
JOBTRAIN:	On-The-Job Training
HELPTRAIN:	Aid From His/Her Employer for Training Outside of Work That is Not Directly Related to His/Her Job
NOHELPTRAIN:	Training for Work w/o the Aid of the Employer?

Table 3. Training variables and associated descriptions from WES Employee survey

2 Human Resource Management (Workplace)

The workplaces surveyed were asked whether they implement any of the following human resource management programs/techniques as shown in Table 4:

Variable Name	Human Resource Practice
HRM1:	Employee Suggestion Program
HRM2:	Flexible Job Design
HRM3:	Information Sharing with employees
HRM4:	Problem Solving Teams
HRM5:	Joint Labor-Management Committees
HRM6:	Self-Directed Work Groups

Table 4. Human Resource Management variables and descriptions from WES Workplace survey

3 Computer Use (Employee)

Employees were asked if they used the technologies listed in Table 5:

Variable Name	Employee Computer Use
COMPUSE:	Computer
TECHUSE:	Computer Controlled/Assisted Technology

Table 5. Computer Use variables and descriptions from from WES Workplace survey

4 Technology (Workplace)

The workplace was asked if any of the following were implemented in the previous year.

Variable Name	Workplace Implementation
TECH1:	New Software/Hardware
TECH2:	Computer Controlled/Assisted Technology
TECH3:	Other Technology

Table 6. Technology variables and associated descriptions from WES Workplace survey

5 Innovation (Workplace)

The workplace was asked if any of the following innovations occurred in the past year (Table 7).

Variable Name	Innovation
NEWPROC:	New process improvement
NEWPROD:	New product improvement
FIRSTINN:	Innovation that is first in the country and/or world

Table 7. Innovation variables and descriptions from WES Workplace survey

6 Education (Employee)

Employers were asked what the minimum level of education that was required for his/her job (Table 8).

Variable EDUC =	**Minimum Level of Education Required for Job**
0	None
1	Elementary School
2	Some Secondary School
3	Secondary School Diploma
4	Some Postsecondary Education
5	Trade Certificate
6	College Diploma
7	University Undergraduate Degree
8	University Professional Accreditation (MD, Law, Architect, Engineer, Education, etc..)
9	University Graduate Degree

Table 8. Education variable and description from WES Emplyee survey

4.2 Experimental Design

1 Industry Level (Workplace)

For the first set of analysis, the data was stratified by industry classification (01-14). The analysis used 5 binary variables associated with the Workplace survey only. It involved technology implementation, introduction of new process and/or product innovation, size of the workplace (i.e. workforce size) and training expenditure.

Variable Name	Description
TECH1:	Implementation of New Hardware/Software
TECH23:	Implementation of Other Technology
TTL_EMPBI:	Number of Employees (Above/Below Industry Average)
PROCPROD:	Introduction of a New Product or Process Innovation
TRNG_EXPBI:	Average Training Expenditure Per Employee (Above/Below Industry Average)

Table 9. Variables and descriptions for industry level analysis of WES Workplace dataset

Here, each variable was constructed by setting it equal to 1 if it satisfied the condition (i.e. for TECH1: if the firm implemented new hardware software in the past year, TECH1=1; otherwise TECH1=0). The cost constraint was created by setting the limiting variable, *g*, equal to the industry average (i.e. mean) of yearly costs of technology implementation (for new hardware/software and other technologies), as collected by each firm participating in the survey. Technology implementation cost data is also collected for each organizational state. This is done by averaging the technology implementation costs for all the firms that have the same organizational state of operations. Thus there are $2^5 = 32$ state costs computed for this model. The cost constraint is then computed by adding all the states' average technology costs and dividing by the total number of states in the optimal path, and this value needs to be less than or equal to the industry average of technology costs for a firm; i.e.

$$\frac{\left(\dfrac{\sum \begin{bmatrix} \text{Yearly technology costs for} \\ \text{each state in the shortest path} \end{bmatrix}}{\text{Number of states in the shortest path}} \right)}{\text{Industry average of yearly technology costs}} \leq \left[\text{Average yearly technology costs of a firm} \right]$$

. So each side constraint coefficient is the industry average technology costs for firms that have that particular state of organizational practices. Thus, any arc that enters a given state has a side (resource) constraint value equal to the industry average cost of technology implementation for all firms with that state of operations.

As a result of the high number of states ($2^5 = 32$), and from stratifying the workplace dataset into 14 separate industries, there were some states that had no observations, otherwise known as empty states. Table 10 gives the percentage of states that were empty for each industry.

Class Number	Industry	Percent of Empty States
01	Forestry, mining, oil, and gas extraction	40.6% (13)
02	Labor intensive tertiary manufacturing	31.3% (10)
03	Primary product manufacturing	25% (8)
04	Secondary product manufacturing	28.1% (9)
05	Capital intensive tertiary manufacturing	28.1% (9)
06	Construction	40.6% (13)
07	Transportation, warehousing, wholesale	31.3% (10)
08	Communication and other utilities	43.8% (14)
09	Retail trade and consumer services	34.4% (11)
10	Finance and insurance	37.5% (12)
11	Real estate, rental and leasing operations	53.1% (17)
12	Business services	40.6% (13)
13	Education and health services	53.1% (17)
14	Information and cultural industries	43.8% (14)

Table 10. Percentage of empty states discovered when creating state variables for CSPP algorithm, by industry classification

2 Employee / Employer Levels

By using both Workplace and Employee data combined, the sample size was greatly increased and allowed for a smaller probability of empty states, thus we could use up to 8 variables to obtain a smaller number of empty states as shown in Table 11. In addition, all analysis was done over all industries aggregated, making the sample sizes even larger.

Run #	Areas Being Analyzed	Number of Vars	Percent of empty states	Variables of Interest
1.	Training	5	0% (0/32)	ClassTrain, JobTrain, HelpTrain, NoHelpTrain
2.	Human Resource Management	6	4.7% (3/64)	HRM1, HRM2, HRM3, HRM4, HRM5, HRM6
3.	Computer Use and Training	6	17.2% (11/64)	ClassTrain, JobTrain, HelpTrain, NoHelpTrain, CompUse, TechUse
4.	ICT and Innovation	6	4.7% (3/64))	Tech1, Tech2, Tech3, NewProc, NewProd, FirstInn
5.	Education and Training	5**	28.1% (45/160)	EDUC, ClassTrain, JobTrain, HelpTrain, NoHelpTrain
6.	Computer Use and Human Resource Management Practices	8	25% (64/256)	CompUse, TechUse, HRM1, HRM2, HRM3, HRM4, HRM5, HRM6

Table 11. Breakdown of variables examined for each management area of interest, and the associated number of empty states discovered

** Note that the EDUC variable is nominal but not binary. Since it takes values from 0 to 9, Run # 5 can produce $2^4 \times 10 = 160$ distinct states, instead of $2^5 = 32$ states if EDUC were binary.

Because the analysis is done without stratifying by industry, the technology cost constraints now use the aggregated average technology costs (i.e. over the whole sample, not stratified by industry).

5 Results

5.1 Algorithm Comparisons

In this section, we compare the CSPP algorithm, in terms of run time, between the three algorithms, Dumitrescu and Boland (D&B), Carlyle, Royset & Wood (CRW), and the CSPP developed for this thesis. These algorithms were created and ran using Matlab on randomly generated problem sets. The number of variables in the graphs are given by |N|, the number of constraints is given by |I|, the number of vertices is given by |V|, and the number of edges is given by |E|. The algorithms were run to optimality as well as within 95% optimality, respectively. This was done in order to compare the algorithms' speed (time) when suboptimal solutions may be adequate for a manager as opposed to when guaranteed optimality is desired.

The D&B algorithm uses a much different approach (label-setting) compared to that developed in this paper and the CRW method (which are LRE methods). It requires more overhead in maintaining labels and doesn't use Lagrangian methods in order to tighten feasibility checks and to create bounds to optimality. The CSPP method differs from the CRW method in that it uses a more general method of subgradient optimization within the LRE framework, performs periodic re-optimizations of the Lagrangian lower bound in order to tighten up the optimality gap faster, and adds extra aggregated bounds in order to perform tighter feasibility checks. These enhancement, although creating more computational overhead, results in an overall speedup of the algorithm due to reaching optimality (or near optimality) in less iterations and less time.

As can be seen in Table 12 and the corresponding Figure 6, for the case of only one constraint (|I|=1), the CSPP algorithm generally outperforms the CRW algorithm. In turn the CRW algorithm generally outperforms the D&B algorithm. These results occur in both the 100% and 95% optimality cases, respectively.

			Run Time (secs) - 100% opt.			Run Time (secs) - 95% opt.		
|N|	**|V|**	**|E|**	**D&B**	**CRW**	**CSPP**	**D&B**	**CRW**	**CSPP**
8	**256**	**704**	0.03	0.01	0.01	0.01	0.01	0.00
9	**512**	**1044**	0.05	0.03	0.02	0.03	0.01	0.01
10	**1024**	**1480**	0.11	0.05	0.04	0.05	0.03	0.01
11	**2048**	**2024**	0.21	0.11	0.09	0.11	0.06	0.03
12	**4096**	**2688**	0.43	0.22	0.18	0.22	0.11	0.05
13	**8192**	**3484**	0.86	0.43	0.36	0.42	0.22	0.11
14	**16384**	**4424**	1.68	0.83	0.72	0.84	0.41	0.21
15	**32768**	**5520**	3.55	1.67	1.42	1.74	0.82	0.43
16	**65536**	**6784**	6.65	3.55	2.84	3.31	1.80	0.82
17	**131072**	**8228**	13.96	7.12	5.87	6.88	3.32	1.71
18	**262144**	**9864**	27.12	13.41	11.27	14.05	7.08	3.59
19	**524288**	**11704**	54.75	27.64	22.78	27.67	13.14	7.03
20	**1048576**	**13760**	107.49	55.82	44.74	55.20	26.54	13.72
21	**2097152**	**16044**	226.19	113.95	96.68	111.52	56.09	27.54
22	**4194304**	**18568**	435.16	226.89	190.23	222.24	107.97	56.35
23	**8388608**	**21344**	909.59	455.42	382.49	455.09	230.24	109.15

Table 12. Runs of Dumitrescu and Boland (D&B) vs. Carlyle & Wood (CRW) vs. CSPP, including relaxing optimization tolerance to 95%, for single constraint systems. i.e |I| = 1

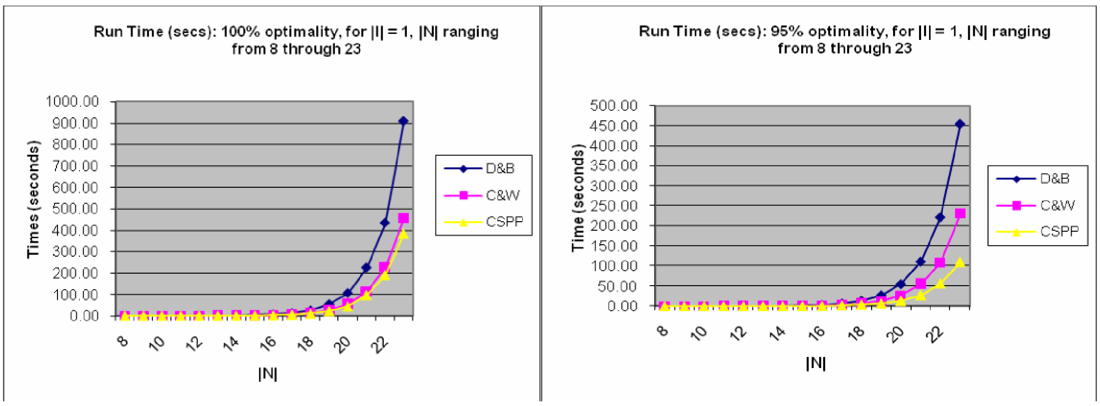

Figure 6. Corresponding plots for runs of Dumitrescu and Boland (D&B) vs. Carlyle, Royset & Wood (CRW) vs. CSPP, including relaxing optimization tolerance to 95%, for single constraint systems. i.e |I| = 1

Figure 7 illustrates the differences in run-time between the three algorithms. Notice that the D&B algorithm benefits the most from dropping to 95% optimality. This is followed by the CSPP algorithm, and then the CRW algorithm, respectively. This makes sense since the D&B algorithm takes the most time to achieve optimality. It's interesting that the CSPP algorithm gains a little more advantage to the CRW algorithm when relaxing the optimality conditions. This could be due to the pre-processing steps used in the CSPP algorithm. Similar results occur when we extend the cases to include |I|=2, 5, 10, and 20.

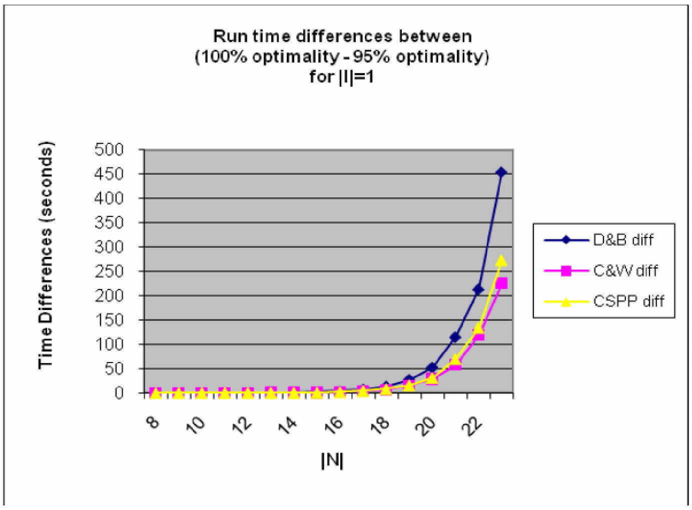

Figure 7. Run time differences between 100% optimality and 95% optimality for CSPP for |I|=1

Table 13 (and Figure 8) shows that when adding another constraint to the randomly generated problems, CSPP continues to outperform the CRW and D&B algorithms, respectively. This occurs for both cases where 100% and 95% optimality is desired.

				Run Time (secs) - 100% opt.			Run Time (secs) - 95% opt.		
|N|	**|V|**	**|E|**	**|I|**	**D&B**	**CRW**	**CSPP**	**D&B**	**CRW**	**CSPP**
8	256	704	2	0.08	0.05	0.05	0.05	0.04	0.04
9	512	1044	2	0.11	0.07	0.07	0.07	0.05	0.04
10	1024	1480	2	0.20	0.12	0.10	0.11	0.08	0.05
11	2048	2024	2	0.37	0.19	0.18	0.20	0.12	0.07
12	4096	2688	2	0.70	0.35	0.32	0.35	0.19	0.11
13	8192	3484	2	1.33	0.71	0.57	0.70	0.36	0.19
14	16384	4424	2	2.67	1.38	1.10	1.27	0.66	0.36
15	32768	5520	2	5.01	2.61	2.14	2.61	1.28	0.68
16	65536	6784	2	10.39	5.21	4.63	5.05	2.59	1.34
17	131072	8228	2	20.32	10.12	9.07	10.60	5.12	2.63
18	262144	9864	2	43.10	21.04	16.87	20.29	10.08	5.38
19	524288	11704	2	80.84	40.39	35.49	39.98	21.01	10.84
20	1048576	13760	2	171.15	80.47	66.73	83.09	41.46	20.13
21	2097152	16044	2	332.97	157.97	136.84	168.83	86.48	40.26
22	4194304	18568	2	687.50	333.47	267.90	344.39	162.17	81.28
23	8388608	21344	2	1282.27	646.07	567.92	686.93	345.09	158.70

Table 13. Runs of Dumitrescu and Boland (D&B) vs. Carlyle, Royset & Wood (CRW) vs. CSPP, including relaxing optimization tolerance to 95%, for 2-constraint systems. i.e |I| = 2

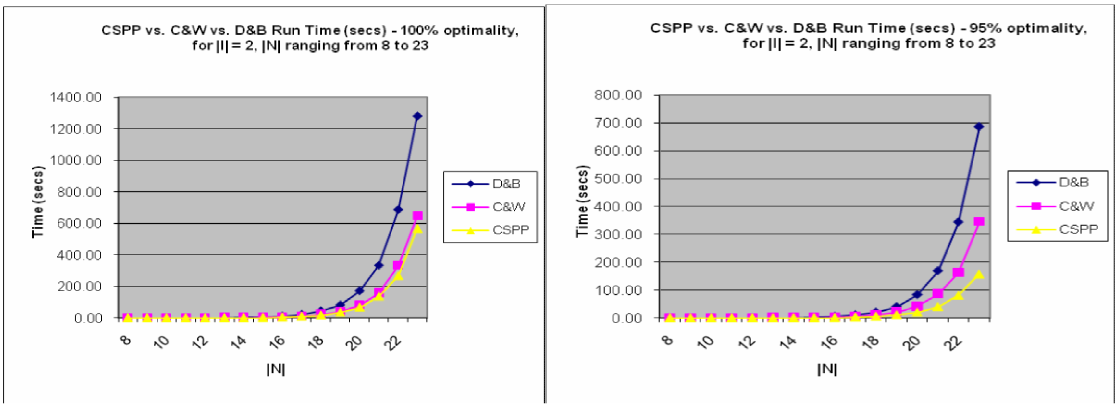

Figure 8. Corresponding plots for runs of Dumitrescu and Boland (D&B) vs. Carlyle, Royset & Wood (CRW) vs. CSPP, including relaxing optimization tolerance to 95%, for 2-constraint systems. i.e |I| = 2

Table 14 and Figure 9 show that when solving randomly generated problems where five constraints exist, CSPP continues to outperform the CRW and D&B algorithms, respectively. This occurs for cases where optimality and within 95% of optimality is desired.

				Run Time (secs) - 100% opt.			Run Time (secs) - 95% opt.		
|N|	**|V|**	**|E|**	**|I|**	**D&B**	**CRW**	**CSPP**	**D&B**	**CRW**	**CSPP**
8	**256**	**704**	**5**	0.17	0.15	0.15	0.15	0.14	0.13
9	**512**	**1044**	**5**	0.21	0.17	0.17	0.17	0.15	0.14
10	**1024**	**1480**	**5**	0.30	0.22	0.20	0.22	0.17	0.15
11	**2048**	**2024**	**5**	0.49	0.31	0.29	0.30	0.21	0.17
12	**4096**	**2688**	**5**	0.85	0.50	0.43	0.47	0.30	0.22
13	**8192**	**3484**	**5**	1.58	0.87	0.75	0.86	0.48	0.30
14	**16384**	**4424**	**5**	2.97	1.62	1.30	1.56	0.83	0.48
15	**32768**	**5520**	**5**	5.69	3.10	2.72	2.88	1.61	0.85
16	**65536**	**6784**	**5**	11.77	5.72	4.82	5.75	3.05	1.56
17	**131072**	**8228**	**5**	23.27	11.99	10.20	12.09	5.82	2.96
18	**262144**	**9864**	**5**	47.57	22.26	20.45	22.52	11.24	5.73
19	**524288**	**11704**	**5**	91.74	44.83	41.18	46.19	23.35	11.84
20	**1048576**	**13760**	**5**	186.72	95.15	82.13	91.95	45.18	23.26
21	**2097152**	**16044**	**5**	349.69	183.42	163.67	188.39	94.77	46.85
22	**4194304**	**18568**	**5**	709.49	356.49	304.40	359.75	174.94	92.12
23	**8388608**	**21344**	**5**	1471.83	750.23	617.65	741.12	372.86	182.59

Table 14. Runs of Dumitrescu and Boland (D&B) vs. Carlyle, Royset & Wood (CRW) vs. CSPP, including relaxing optimization tolerance to 95%, for 5-constraint systems. i.e |I| = 5

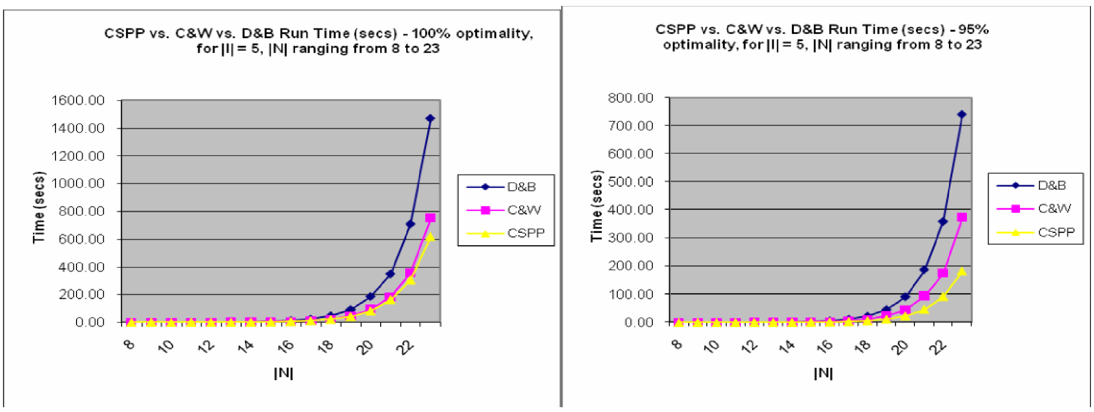

Figure 9. Corresponding plots for runs of Dumitrescu and Boland (D&B) vs. Carlyle, Royset & Wood (CRW) vs. CSPP, including relaxing optimization tolerance to 95%, for 5-constraint systems. i.e |I| = 5

Table 15 and Figure 10 show that when solving randomly generated problems where ten constraints exist, CSPP continues to outperform the CRW and D&B algorithms, respectively. This occurs for cases where optimality and within 95% of optimality is desired.

				Run Time (secs) - 100% opt.			Run Time (secs) - 95% opt.		
|N|	**|V|**	**|E|**	**|I|**	**D&B**	**CRW**	**CSPP**	**D&B**	**CRW**	**CSPP**
8	**256**	**704**	**10**	3.01	2.95	2.94	2.95	2.92	2.90
9	**512**	**1044**	**10**	3.15	3.02	3.00	3.01	2.95	2.92
10	**1024**	**1480**	**10**	3.41	3.14	3.12	3.16	3.01	2.95
11	**2048**	**2024**	**10**	3.95	3.40	3.34	3.44	3.14	3.02
12	**4096**	**2688**	**10**	4.99	3.99	3.77	3.98	3.44	3.16
13	**8192**	**3484**	**10**	7.34	5.01	4.81	5.02	3.96	3.40
14	**16384**	**4424**	**10**	11.24	7.07	6.53	7.37	4.99	3.94
15	**32768**	**5520**	**10**	19.38	11.25	10.52	11.83	7.21	5.08
16	**65536**	**6784**	**10**	36.21	20.48	17.46	20.86	11.21	7.38
17	**131072**	**8228**	**10**	74.32	36.79	32.72	36.24	20.17	11.75
18	**262144**	**9864**	**10**	140.23	73.16	59.68	70.63	37.64	20.77
19	**524288**	**11704**	**10**	287.40	144.25	126.87	134.36	70.70	38.69
20	**1048576**	**13760**	**10**	576.44	289.68	246.81	273.44	139.66	73.62
21	**2097152**	**16044**	**10**	1138.26	573.92	478.43	578.63	279.11	134.52
22	**4194304**	**18568**	**10**	2171.57	1059.21	902.68	1131.28	539.60	271.47
23	**8388608**	**21344**	**10**	4571.07	2168.93	1868.92	2165.14	1077.13	557.32

Table 15. Runs of Dumitrescu and Boland (D&B) vs. Carlyle, Royset & Wood (CRW) vs. CSPP, including relaxing optimization tolerance to 95%, for 10-constraint systems. i.e |I| = 10

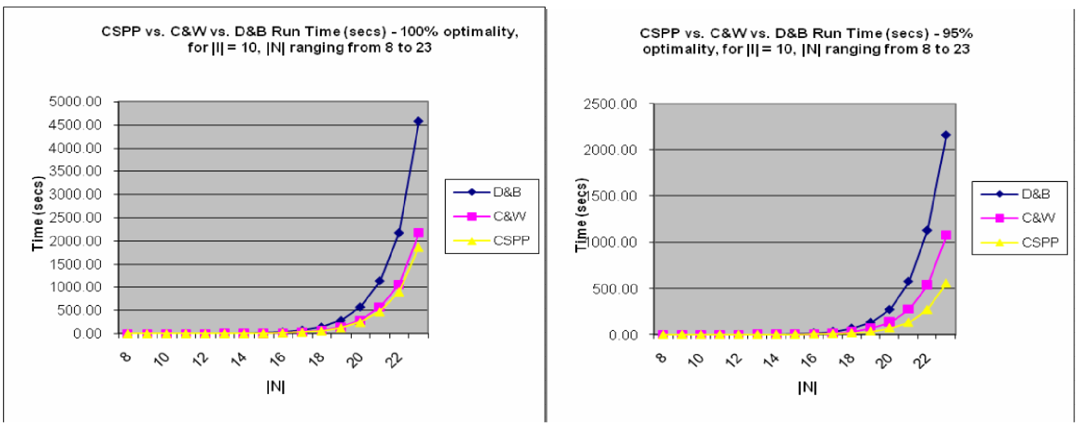

Figure 10. Corresponding plots for runs of Dumitrescu and Boland (D&B) vs. Carlyle, Royset & Wood (CRW) vs. CSPP, including relaxing optimization tolerance to 95%, for 10-constraint systems. i.e |I| = 10

Table 16 and Figure 11 shows that when solving randomly generated problems where twenty constraints exist, CSPP continues to outperform the CRW and D&B algorithms, respectively. This occurs for cases where optimality and within 95% of optimality is desired.

				Run Time (secs) - 100% opt.			Run Time (secs) - 95% opt.		
|N|	|V|	|E|	|I|	D&B	CRW	CSPP	D&B	CRW	CSPP
8	256	704	20	8.87	9.12	7.23	9.38	8.61	9.21
9	512	1044	20	7.44	7.81	8.57	6.75	7.43	7.37
10	1024	1480	20	8.44	8.11	6.70	9.92	9.71	6.96
11	2048	2024	20	12.26	10.63	7.43	10.50	9.19	8.89
12	4096	2688	20	15.97	11.20	9.45	11.90	10.45	7.78
13	8192	3484	20	20.98	16.12	10.95	11.77	9.27	8.94
14	16384	4424	20	30.92	18.23	17.77	21.28	16.01	9.10
15	32768	5520	20	49.71	29.02	28.82	34.13	18.82	12.38
16	65536	6784	20	105.08	50.93	49.95	53.53	32.95	16.92
17	131072	8228	20	189.88	115.55	99.95	122.17	53.01	34.98
18	262144	9864	20	466.30	206.75	159.29	217.09	119.52	52.81
19	524288	11704	20	883.96	364.64	316.92	450.91	183.66	111.73
20	1048576	13760	20	1673.75	841.44	482.94	831.03	310.50	197.65
21	2097152	16044	20	2709.98	1278.13	1065.61	1328.30	683.76	371.85
22	4194304	18568	20	5048.32	3200.29	2101.08	2768.29	1509.29	823.37
23	8388608	21344	20	11547.77	7064.22	5465.22	5389.22	2635.34	1303.11

Table 16. Runs of Dumitrescu and Boland (D&B) vs. Carlyle & Wood (CRW) vs. CSPP, including relaxing optimization tolerance to 95%, for 20-constraint systems. i.e |I| = 20

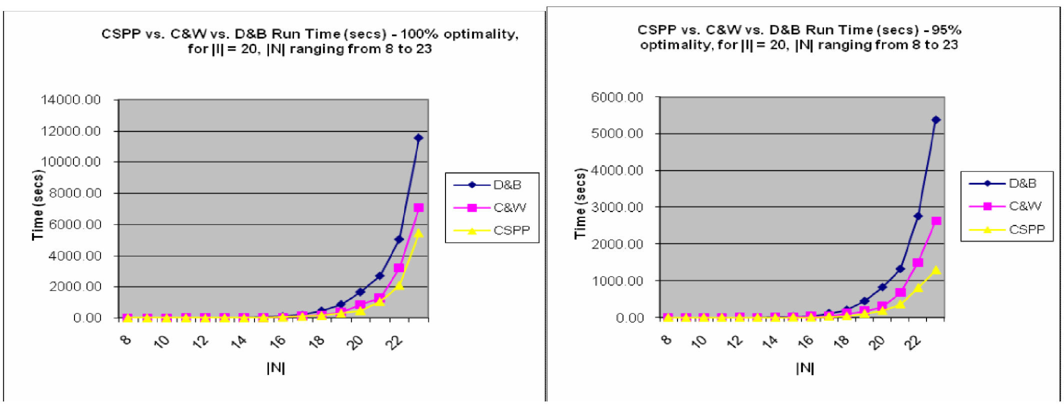

Figure 11. Plots for runs of Dumitrescu and Boland (D&B) vs. Carlyle, Royset & Wood (CRW) vs. CSPP, including relaxing optimization tolerance to 95%, for 20-constraint systems. i.e |I| = 20

Overall, we can see that the CSPP algorithm outperforms other leading algorithms (i.e. D&B and CRW) for these randomly generated problems. The time differences are fairly consistent between the algorithms. We see that the CRW algorithm performs closer to the CSPP algorithm for 100% optimality and lesser so for 95% optimality, suggesting that the CSPP algorithm gains more advantage over CRW algorithm as the optimality requirements are relaxed.

These results generally support the idea of creating tighter bounds by both tightening the optimality gap through periodic re-optimization of the lower bound and by creating more feasibility checks by further subdividing the side constraint weights on the edges of the graph. Subgradient optimization didn't appear to add any significant difference compared to the bisection search of the CRW method for relatively small number of side constraints, but should generally improve the algorithm as the number of side constraints grows larger. One of the major advantages of the CRW method is that it uses a fast near-shortest path method of enumerating the edges. The D&W algorithm suffers the drawbacks that it doesn't make use of Lagrangian techniques and has high overhead with maintaining labels, as is required in label-setting algorithms.

5.2 Workplace and Employee Survey Section[15]

5.2.1 Computer Use, ICT, Innovation, Training, Education, and Human Resource Management (Aggregate Results Over All Industries)

In this section, we examine specific areas of organizational management, including computer use, ICT, innovation, training, education, and human resource management. We examine them individually as well as in combination (e.g. computer use and

[15] See Appendix B for state mean values for the performance variables as well as the overall mean values (by industry) associated with the results in this section.

training), using the same techniques as in the previous section. Every section below, the static variables (i.e. profit and labor productivity) are analyzed using all years of data, 1999-2004. For the growth variables (i.e. profit growth and labor productivity growth), all year-to-year periods, 1999-2000 through 2003-2004, are used in completing the analysis. In addition, all industries are grouped together. Using all the available years of data and aggregating over all industries helped in obtaining significant results. More specifically, this resulted in fewer instances of zero-states (i.e. states of operation with no firms represented).

1 Training

In regards to training, the binary order (from left to right) of variables discussed in this section are as follows: **CLASSTRAIN, JOBTRAIN, HELPTRAIN, NOHELPTRAIN.** The training techniques were analyzed to discover which organizational decisions lead to optimal training practices. The yes/no questions regarding each of the variables are as follows:

CLASSTRAIN: Has the employee received (in the past year) formal training in the classroom?

JOBTRAIN: Has the employee received (in the past year) on-the-job training?

HELPTRAIN: Has the employee received (in the past year) aid from his/her employer for training outside of work that is not directly related to his/her job?

NOHELPTRAIN: Has the employee received (in the past year) training for work w/o the aid of the employer?

The associated state numbers used in the following discussion relates to the characteristics described in Table 17.

State Number (Decimal)	Binary Value	CLASSTRAIN?	JOBTRAIN?	HELPTRAIN?	NOHELPTRAIN?
0	0000	No	No	No	No
1	0001	No	No	No	Yes
2	0010	No	No	Yes	No
3	0011	No	No	Yes	Yes
4	0100	No	Yes	No	No
5	0101	No	Yes	No	Yes
6	0110	No	Yes	Yes	No
7	0111	No	Yes	Yes	Yes
8	1000	Yes	No	No	No
9	1001	Yes	No	No	Yes
10	1010	Yes	No	Yes	No
11	1011	Yes	No	Yes	Yes
12	1100	Yes	Yes	No	No
13	1101	Yes	Yes	No	Yes
14	1110	Yes	Yes	Yes	No
15	1111	Yes	Yes	Yes	Yes

Table 17. State number (decimal and binary) representations and their associated training-related characteristics (for results over all industries).

Referring to Table 18, for profit growth, we see a transition from 4 (0100 – on-the-job training only) to 6 (0110 – on-the-job training and employer-aided non-work-related training). This suggests that on-the-job training is best coupled with outside of work training not directly related to his/her job. There appears to be a large gap in performance between on-the-job training on its own compared to the aforementioned coupling. For labor productivity growth, we see a transition from 1 (0001 – training for work w/o aid from employer) to 3 (0011 - employer-aided non-work-related training and training for work w/o aid from employer). This suggests that outside of work training not directly related to his/her job is best coupled with work-related training outside of the workplace.

For profit margin we see a transition from 7 (0111 - on-the-job training, employer-aided non-work-related training, and training for work w/o aid from employer) to 15 (1111 – all 4 forms of training implemented). Again, one change to state 7 by adding formal training seems to make a big difference in profit. For labor productivity, we see a transition from 1 (0001 - training for work w/o aid from employer) to 3 (0011 - employer-aided non-work-related training and training for work w/o aid from employer). One change from state 1 to state 3 by adding help for training outside of work along with self-paid training outside of work makes a big difference in performance.

The productivity measures seem to be at a maximum with help for training outside work or self-paid training, whereas there doesn't seem to be a clear-cut solution for the profit measure. All the cases above involve only one operational change to move from the weakest state to the strongest state. This is very efficient for businesses that previously were working in the weakest state of operations.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	4	-139.4476	6	1512.77	4-6
glprod	% change per employee	1	0.6564853	3	4.4286209	1-3
profit	$ per employee	7	0.1806262	15	2.1521788	7-15
lprod	$ per employee	1	149844.33	3	402844.51	1-3

Table 18. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (Training variables).

The literature regarding training would suggest in general that the more trained a workforce is, the more productivity and more profitable the firm would be. This is confirmed for the profit measure, but not so for the other measures, where only a subset of training practices are recommended. The reasoning behind this could be further fleshed out by running the analysis for each industry.

2 Human Resource Management

In regards to human resource management (HRM) techniques, the binary order of variables described are as follows: **HRM1, HRM2, HRM3, HRM4, HRM5, HRM6.** The techniques were analyzed to discover which organizational decisions in regards to HRM leads to optimal practices. The yes/no questions regarding whether the workplace implements any of the following human resource management programs/techniques:

HRM1: Employee Suggestion Program

HRM2: Flexible Job Design

HRM3: Information Sharing with employees

HRM4: Problem Solving Teams

HRM5: Joint labor-management committees

HRM6: Self-directed work groups

The associated state numbers used in the following discussion relates to the characteristics described in Table 19.

State Number (Decimal)	Binary Value	HRM1?	HRM2?	HRM3?	HRM4?	HRM5?	HRM6?
0	000000	No	No	No	No	No	No
1	000001	No	No	No	No	No	Yes
2	000010	No	No	No	No	Yes	No
3	000011	No	No	No	No	Yes	Yes
4	000100	No	No	No	Yes	No	No
5	000101	No	No	No	Yes	No	Yes
6	000110	No	No	No	Yes	Yes	No
7	000111	No	No	No	Yes	Yes	Yes
8	001000	No	No	Yes	No	No	No
9	001001	No	No	Yes	No	No	Yes
10	001010	No	No	Yes	No	Yes	No
11	001011	No	No	Yes	No	Yes	Yes
12	001100	No	No	Yes	Yes	No	No
13	001101	No	No	Yes	Yes	No	Yes
14	001110	No	No	Yes	Yes	Yes	No
15	001111	No	No	Yes	Yes	Yes	Yes
16	010000	No	Yes	No	No	No	No
17	010001	No	Yes	No	No	No	Yes
18	010010	No	Yes	No	No	Yes	No
19	010011	No	Yes	No	No	Yes	Yes
20	010100	No	Yes	No	Yes	No	No
21	010101	No	Yes	No	Yes	No	Yes
22	010110	No	Yes	No	Yes	Yes	No
23	010111	No	Yes	No	Yes	Yes	Yes
24	011000	No	Yes	Yes	No	No	No
25	011001	No	Yes	Yes	No	No	Yes
26	011010	No	Yes	Yes	No	Yes	No
27	011011	No	Yes	Yes	No	Yes	Yes
28	011100	No	Yes	Yes	Yes	No	No
29	011101	No	Yes	Yes	Yes	No	Yes
30	011110	No	Yes	Yes	Yes	Yes	No
31	011111	No	Yes	Yes	Yes	Yes	Yes
32	100000	Yes	No	No	No	No	No
33	100001	Yes	No	No	No	No	Yes
34	100010	Yes	No	No	No	Yes	No
35	100011	Yes	No	No	No	Yes	Yes
36	100100	Yes	No	No	Yes	No	No
37	100101	Yes	No	No	Yes	No	Yes
38	100110	Yes	No	No	Yes	Yes	No

Table 19. State number (decimal and binary) representations and their associated HRM-related characteristics (for results over all industries).
***Table continued on next page**

State Number (Decimal)	Binary Value	HRM1?	HRM2?	HRM3?	HRM4?	HRM5?	HRM6?
39	100111	Yes	No	No	Yes	Yes	Yes
40	101000	Yes	No	Yes	No	No	No
41	101001	Yes	No	Yes	No	No	Yes
42	101010	Yes	No	Yes	No	Yes	No
43	101011	Yes	No	Yes	No	Yes	Yes
44	101100	Yes	No	Yes	Yes	No	No
45	101101	Yes	No	Yes	Yes	No	Yes
46	101110	Yes	No	Yes	Yes	Yes	No
47	101111	Yes	No	Yes	Yes	Yes	Yes
48	110000	Yes	Yes	No	No	No	No
49	110001	Yes	Yes	No	No	No	Yes
50	110010	Yes	Yes	No	No	Yes	No
51	110011	Yes	Yes	No	No	Yes	Yes
52	110100	Yes	Yes	No	Yes	No	No
53	110101	Yes	Yes	No	Yes	No	Yes
54	110110	Yes	Yes	No	Yes	Yes	No
55	110111	Yes	Yes	No	Yes	Yes	Yes
56	111000	Yes	Yes	Yes	No	No	No
57	111001	Yes	Yes	Yes	No	No	Yes
58	111010	Yes	Yes	Yes	No	Yes	No
59	111011	Yes	Yes	Yes	No	Yes	Yes
60	111100	Yes	Yes	Yes	Yes	No	No
61	111101	Yes	Yes	Yes	Yes	No	Yes
62	111110	Yes	Yes	Yes	Yes	Yes	No
63	111111	Yes	Yes	Yes	Yes	Yes	Yes

Table 19 (continued from previous page). State number (decimal and binary) representations and their associated HRM-related characteristics (for results over all industries).

As displayed in Table 20, for profit growth, we see a transition from 2 (000010) to 43 (101011). This transition corresponds to starting with joint labor-management committees, adding self-directed work groups, adding information sharing with employees, then adding an employee suggestion program. This suggests that having joint labor-management committees alone is a weak practice; It is much better to include this practice with an employee suggestion program, information sharing, and self-directed work groups. For labor productivity growth, we see a transition from 23 (010111) to 17

(010001). This corresponds to starting with [flexible job design, problem solving teamsn, joint labor-management committees, and self-directed work groups], removing problem solving teams, and removing joint labor-management committees. This suggests that flexible job design coupled with self-directed work groups is superior to adding problem solving teams and joint labor-management committees.

For profit margin we see a transition from 53 (110101) to 51 (110011). This corresponds to starting with [employee suggestion program, flexible job design, problem solving teams, self-directed work groups], adding joint labor-management committees, and removing problem solving teams. This suggests that the combination of an employee suggestion program, flexible job design, problem solving teams and self-directed work groups is weak compared to the combination of an employee suggestion program, flexible job design, joint labor-management committees, and self-directed work groups. They are quite similar but when replacing problem solving teams with joint labor-management committees, profit improves. For labor productivity, we see a transition from 49 (110001) to 18 (010010). This corresponds to starting with [employee suggestion program, flexible job design, and self-directed work groups], adding joint labor-management committees, removing self-directed work groups, and removing the employee suggestion program. This suggests that having flexible job design is ideal when coupled with joint labor-management committees.

Overall, we still see different strategies being optimal (and different strategies being weak) depending on the measure of performance used. However, we don't see any overlap between states that are optimal under one measure and conversely weakest on another.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	**% change per employee**	2	-1124.05	43	427.86306	2-3-11-43
glprod	**% change per employee**	23	-0.823241	17	7.6476929	23-19-17
profit	**$ per employee**	53	-0.074922	51	3.340858	53-55-51
lprod	**$ per employee**	49	84774	18	885066.44	49-51-50-18

Table 20. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (Human Resource Management variables).

A unique feature of the WES dataset is that the respondents were asked when they first implemented each of the practices. This allowed us to examine for each firm the order in which firms adopted these practices. As a result, we found that approximately 87% of firms in Canada adopted all these practices in the same year, according to the 2003 WES dataset. This is further illustrated in Table 21, where it is shown that the mean year for implementation among the individual HRM practices are between 1993 and 1995. The general order of adoption from this data suggests that firms implement the practices in order of HRM2-HRM3-HRM6-HRM5-HRM2-HRM4. Since none of the shortest paths found involved keeping all of the HRM practices, there isn't much correlation between the data and what is done in practice. This gives some further evidence that firms could use a path-dependent method for determining how to organize their future adoptions of organizational practices.

	Employee suggestion program	Flexible job design	Information sharing with employees	Problem-solving teams	Joint Labour-management committees	Self-directed work groups
Variable :	**HRM1**	**HRM2**	**HRM3**	**HRM4**	**HRM5**	**HRM6**
Year (Avg):	1993.99	1994.39	1993.58	1994.85	1993.78	1993.63

Table 21. Year of first implementation of each human resource management practices from the 2003 WES survey (aggregated over all industries)

3 Computer Use and Training

In this section the order of the variables are: **COMPUSE, TECHUSE, CLASSTRAIN, JOBTRAIN, HELPTRAIN, NOHELPTRAIN.** Here, computer use and training techniques (mentioned in section 1) were analyzed together to discover which organizational decisions in regards to the two areas leads to optimal practices.

The computer use variables are as follows (pertaining to the previous year):

COMPUSE: Does the employee use a computer?

TECHUSE: Does the employee use computer controlled/assisted technology?

The associated state numbers used in the following discussion relates to the characteristics described in Table 22.

State Number (Decimal)	Binary Value	COMPUSE?	TECHUSE?	CLASSTRAIN?	JOBTRAIN?	HELPTRAIN?	NOHELPTRAIN?
0	000000	No	No	No	No	No	No
1	000001	No	No	No	No	No	Yes
2	000010	No	No	No	No	Yes	No
3	000011	No	No	No	No	Yes	Yes
4	000100	No	No	No	Yes	No	No
5	000101	No	No	No	Yes	No	Yes
6	000110	No	No	No	Yes	Yes	No
7	000111	No	No	No	Yes	Yes	Yes
8	001000	No	No	Yes	No	No	No
9	001001	No	No	Yes	No	No	Yes
10	001010	No	No	Yes	No	Yes	No
11	001011	No	No	Yes	No	Yes	Yes
12	001100	No	No	Yes	Yes	No	No
13	001101	No	No	Yes	Yes	No	Yes
14	001110	No	No	Yes	Yes	Yes	No
15	001111	No	No	Yes	Yes	Yes	Yes
16	010000	No	Yes	No	No	No	No
17	010001	No	Yes	No	No	No	Yes
18	010010	No	Yes	No	No	Yes	No
19	010011	No	Yes	No	No	Yes	Yes
20	010100	No	Yes	No	Yes	No	No
21	010101	No	Yes	No	Yes	No	Yes
22	010110	No	Yes	No	Yes	Yes	No
23	010111	No	Yes	No	Yes	Yes	Yes
24	011000	No	Yes	Yes	No	No	No
25	011001	No	Yes	Yes	No	No	Yes
26	011010	No	Yes	Yes	No	Yes	No
27	011011	No	Yes	Yes	No	Yes	Yes
28	011100	No	Yes	Yes	Yes	No	No
29	011101	No	Yes	Yes	Yes	No	Yes
30	011110	No	Yes	Yes	Yes	Yes	No
31	011111	No	Yes	Yes	Yes	Yes	Yes
32	100000	Yes	No	No	No	No	No
33	100001	Yes	No	No	No	No	Yes
34	100010	Yes	No	No	No	Yes	No
35	100011	Yes	No	No	No	Yes	Yes
36	100100	Yes	No	No	Yes	No	No
37	100101	Yes	No	No	Yes	No	Yes
38	100110	Yes	No	No	Yes	Yes	No

Table 22. State number (decimal and binary) representations and their associated computer use and training-related characteristics (for results over all industries).

***Table continued on next page**

State Number (Decimal)	Binary Value	COMPUSE?	TECHUSE?	CLASSTRAIN?	JOBTRAIN?	HELPTRAIN?	NOHELPTRAIN?
39	100111	Yes	No	No	Yes	Yes	Yes
40	101000	Yes	No	Yes	No	No	No
41	101001	Yes	No	Yes	No	No	Yes
42	101010	Yes	No	Yes	No	Yes	No
43	101011	Yes	No	Yes	No	Yes	Yes
44	101100	Yes	No	Yes	Yes	No	No
45	101101	Yes	No	Yes	Yes	No	Yes
46	101110	Yes	No	Yes	Yes	Yes	No
47	101111	Yes	No	Yes	Yes	Yes	Yes
48	110000	Yes	Yes	No	No	No	No
49	110001	Yes	Yes	No	No	No	Yes
50	110010	Yes	Yes	No	No	Yes	No
51	110011	Yes	Yes	No	No	Yes	Yes
52	110100	Yes	Yes	No	Yes	No	No
53	110101	Yes	Yes	No	Yes	No	Yes
54	110110	Yes	Yes	No	Yes	Yes	No
55	110111	Yes	Yes	No	Yes	Yes	Yes
56	111000	Yes	Yes	Yes	No	No	No
57	111001	Yes	Yes	Yes	No	No	Yes
58	111010	Yes	Yes	Yes	No	Yes	No
59	111011	Yes	Yes	Yes	No	Yes	Yes
60	111100	Yes	Yes	Yes	Yes	No	No
61	111101	Yes	Yes	Yes	Yes	No	Yes
62	111110	Yes	Yes	Yes	Yes	Yes	No
63	111111	Yes	Yes	Yes	Yes	Yes	Yes

Table 22 (continued from previous page). State number (decimal and binary) representations and their associated computer use and training-related characteristics (for results over all industries).

Referring to Table 23, for profit growth, we see a transition from 36 (100100) to 54 (110110). This corresponds to starting with [employee computer use and on-the-job training], adding employee use of computer controlled/assisted technology, and adding employer-aided non-work-related training. This suggests that computers and computer technology, when combined with on-the-job training and unrelated, supported job training outside of the workplace for employees leads to high overall workplace performance. For labor productivity growth, we see a transition from 30 (011110) to 43 (101011). This corresponds to starting with [employee use of computer controlled/assisted technology, classroom training, on-the-job training, and employer-aided non-work-related training], removing classroom training, removing on-the-job training, adding training for work w/o aid from employer, and adding employee computer use. This suggests that computer use, formal training, and outside training (both related and unrelated to the job) make for a combination that is supportive of optimal growth in terms of labor productivity.

For profit margin we see a transition from 25 (011001) to 54 (110110). This corresponds to starting with [employee use of computer controlled/assisted technology, classroom training, and training for work w/o aid from employer], remove classroom training, remove training for work w/o aid from employer, add employer-aided non-work-related training, add on-the-job training, and add employee computer use.

This suggests that the same optimal combination of computer use and training as seen for profit growth is also optimal for the profit measure. For labor productivity, we see a transition from 30 (011110) to 43 (101011). This corresponds to starting with [employee computer use and on-the-job training], adding employee use of computer controlled/assisted technology, and adding employer-aided non-work-related training. This is the same optimal combination as for the growth variable of labor productivity. Also, the two productivity measures weakest states, thus the paths are identical as well.

The results of computer use and training shows strong connections between the profit variables, as well as even stronger connections between the productivity variables. This suggests that there are two distinct sets of optimal states, depending on whether profit (and/or profit growth) are of most concern, or if productivity (and/or growth of productivity) are of concern. The results also show that adding training and technology adoption in some combination is preferred, as the literature suggests.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	36	-250.4572	54	7852.77	36-52-54
glprod	% change per employee	30	-0.804981	43	9.1540786	30-14-10-11-43
profit	$ per employee	25	-0.113125	54	2.6963176	25-17-16-18-22-54
lprod	$ per employee	30	48743.7	43	659627.51	30-14-10-11-43

Table 23. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (Computer Use and Training).

4 ICT and Innovation

In this section the order of the variables examined are: **TECH1, TECH2, TECH3, NEWPROC, NEWPROD, FIRSTINN**. Here, ICT and innovation were analyzed together to discover which organizational decisions in regards to the two areas leads to optimal practices. The Technology and innovation variables answer the following yes/no questions (pertaining to the previous year):

TECH1: Was there an implementation of new software/hardware?

Tech2: Was there an implementation of computer controlled/assisted technology?

TECH3: Was there an implementation of other technology?

NEWPROC: Was there an new process improvement?

NEWPROD: Was there an new product improvement?

FIRSTINN: Was there an innovation that is first in the country or world?

The associated state numbers used in the following discussion relates to the characteristics described in Table 24.

State Number (Decimal)	Binary Value	TECH1?	TECH2?	TECH3?	NEWPROC?	NEWPROD?	FIRSTINN?
0	000000	No	No	No	No	No	No
1	000001	No	No	No	No	No	Yes
2	000010	No	No	No	No	Yes	No
3	000011	No	No	No	No	Yes	Yes
4	000100	No	No	No	Yes	No	No
5	000101	No	No	No	Yes	No	Yes
6	000110	No	No	No	Yes	Yes	No
7	000111	No	No	No	Yes	Yes	Yes
8	001000	No	No	Yes	No	No	No
9	001001	No	No	Yes	No	No	Yes
10	001010	No	No	Yes	No	Yes	No
11	001011	No	No	Yes	No	Yes	Yes
12	001100	No	No	Yes	Yes	No	No
13	001101	No	No	Yes	Yes	No	Yes
14	001110	No	No	Yes	Yes	Yes	No
15	001111	No	No	Yes	Yes	Yes	Yes
16	010000	No	Yes	No	No	No	No
17	010001	No	Yes	No	No	No	Yes
18	010010	No	Yes	No	No	Yes	No
19	010011	No	Yes	No	No	Yes	Yes
20	010100	No	Yes	No	Yes	No	No
21	010101	No	Yes	No	Yes	No	Yes
22	010110	No	Yes	No	Yes	Yes	No
23	010111	No	Yes	No	Yes	Yes	Yes
24	011000	No	Yes	Yes	No	No	No
25	011001	No	Yes	Yes	No	No	Yes
26	011010	No	Yes	Yes	No	Yes	No
27	011011	No	Yes	Yes	No	Yes	Yes
28	011100	No	Yes	Yes	Yes	No	No
29	011101	No	Yes	Yes	Yes	No	Yes
30	011110	No	Yes	Yes	Yes	Yes	No
31	011111	No	Yes	Yes	Yes	Yes	Yes

Table 24. State number (decimal and binary) representations and their associated ICT and innovation-related characteristics (for results over all industries).
***Table continued on next page**

State Number (Decimal)	Binary Value	TECH1?	TECH2?	TECH3?	NEWPROC?	NEWPROD?	FIRSTINN?
32	100000	Yes	No	No	No	No	No
33	100001	Yes	No	No	No	No	Yes
34	100010	Yes	No	No	No	Yes	No
35	100011	Yes	No	No	No	Yes	Yes
36	100100	Yes	No	No	Yes	No	No
37	100101	Yes	No	No	Yes	No	Yes
38	100110	Yes	No	No	Yes	Yes	No
39	100111	Yes	No	No	Yes	Yes	Yes
40	101000	Yes	No	Yes	No	No	No
41	101001	Yes	No	Yes	No	No	Yes
42	101010	Yes	No	Yes	No	Yes	No
43	101011	Yes	No	Yes	No	Yes	Yes
44	101100	Yes	No	Yes	Yes	No	No
45	101101	Yes	No	Yes	Yes	No	Yes
46	101110	Yes	No	Yes	Yes	Yes	No
47	101111	Yes	No	Yes	Yes	Yes	Yes
48	110000	Yes	Yes	No	No	No	No
49	110001	Yes	Yes	No	No	No	Yes
50	110010	Yes	Yes	No	No	Yes	No
51	110011	Yes	Yes	No	No	Yes	Yes
52	110100	Yes	Yes	No	Yes	No	No
53	110101	Yes	Yes	No	Yes	No	Yes
54	110110	Yes	Yes	No	Yes	Yes	No
55	110111	Yes	Yes	No	Yes	Yes	Yes
56	111000	Yes	Yes	Yes	No	No	No
57	111001	Yes	Yes	Yes	No	No	Yes
58	111010	Yes	Yes	Yes	No	Yes	No
59	111011	Yes	Yes	Yes	No	Yes	Yes
60	111100	Yes	Yes	Yes	Yes	No	No
61	111101	Yes	Yes	Yes	Yes	No	Yes
62	111110	Yes	Yes	Yes	Yes	Yes	No
63	111111	Yes	Yes	Yes	Yes	Yes	Yes

Table 24 (Continued from previous page). State number (decimal and binary) representations and their associated ICT and innovation-related characteristics (for results over all industries).

In reference to Table 25, for profit growth, we see a transition from 40 (101000) to 4 (000100). This corresponds to starting with [implementing new software/hardware and implementing other technology], stop implementing other technology, stop implementing new software/hardware, and then create a new process improvement. This suggests that new implementations of technology (hardware/software and other technology) are less effective than new process improvement. This suggests that new process improvements should take priority in general. For labor productivity growth, we see a transition from 49 (110001) to 11 (001011). This corresponds to starting with [implementing new software/hardware, implementing computer controlled/assisted technology, and creating a first in country and/or world innovation], stop implementing new software/hardware, and then creating a new product improvement. This suggests that other technologies coupled with a world or country first innovation should also be supported with a new product improvement, and definitely not with an implementation of new hardware/software and computer controlled/assisted technology. Ideally, a business should operate in state 19 (010011), that is [implementing computer controlled/assisted technology, creating a new product improvement, creating a first in country and/or world innovation], but that is not feasible due to the cost constraint.

For profit margin we see a transition from 59 (111011) to 3 (000011). This corresponds to starting with [implementing new software/hardware, implementing computer controlled/assisted technology, implementing other technology, creating a new product improvement, creating a first in country and/or world innovation], stop implementing computer controlled/assisted technology, stop implementing other technology, and stop implementing new software/hardware. This suggests that a product improvement along with a world or country first innovation will yield high profits. This is not quite as high as state 37 (i.e. [implementing new software/hardware, creating a new process improvement, creating a first in country and/or world innovation]), which is unattainable due to cost constraints, which comes from implementing new hardware/software. For labor productivity, we see a transition from 49 (110001) to 9 (001001). This corresponds to starting with [implementing new software/hardware, implementing computer controlled/assisted technology, and creating a first in country and/or world innovation], stop implementing new computer controlled/assisted technology, stop implementing new software/hardware, and then implement other technology. This recommends that other technologies be implemented along with a world or country first innovation.

This section gave insight that in terms of productivity (and growth of productivity) implementing new hardware/software and computer controlled/assisted technologies along with having a world or country first innovation does not generally lead to good results. This goes against economic theory that would suggest innovation and new technology would generally work well in combination. Otherwise, there are many combinations that seem to produce reasonably good results, but no overwhelming strategy was determined.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	40	-52.96409	4	377.30883	40-32-0-4
glprod	% change per employee	49	-0.13527	11	16.656736	49-17-19*
profit	$ per employee	59	-0.001751	37	1.9872589	59-43-35-3*
lprod	$ per employee	49	66152.58	45	809384.06	49-33-1-9*

Table 25. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (ICT and Innovation).
*** max state unattainable due to budget constraint**

5 Education and Training

The order of variables while analyzing education and training firm characteristics were as follows: **EDUC, CLASSTRAIN, JOBTRAIN, HELPTRAIN, NOHELPTRAIN**. They were analyzed together to discover which organizational characteristics decisions in regards to the two areas leads to optimal performances. The education variable is defined as with the answer to the following question:

EDUC: What is the minimum level of education required for this job?

Responses:

0 None

1 Elementary school

2 Some secondary school

3 Secondary school diploma

4 Some postsecondary education

5 Trade certificate

6 College diploma

7 University undergraduate degree

8 University professional accreditation (MD, Law, Architect, Engineer, Education, etc..)

9 University graduate degree

The associated state numbers used in the following discussion relates to the characteristics described in Table 26. Due to the nominal values of the education variable (EDUC), the overall binary representation used to represent education and training is different than what has previous been discussed. The first 4 binary numbers in the string (from left to right) represent the EDUC variable (e.g. 1001 represents a university graduate degree). Since the other 4 variables are binary, they are represented the same way as previously discussed (e.g. 1100 represents the implementation of classroom training and on-the-job training). Thus a binary string of 10011100 (decimal value 140) represents possessing a university graduate degree as well as receiving classroom and on-the-job training within the last year.

State Number (Decimal)	Binary Value	EDUC (code Number)	CLASSTRAIN?	JOBTRAIN?	HELPTRAIN?	NOHELPTRAIN?
0	00000000	0	No	No	No	No
1	00000001	0	No	No	No	Yes
2	00000010	0	No	No	Yes	No
3	00000011	0	No	No	Yes	Yes
4	00000100	0	No	Yes	No	No
5	00000101	0	No	Yes	No	Yes
6	00000110	0	No	Yes	Yes	No
7	00000111	0	No	Yes	Yes	Yes
8	00001000	0	Yes	No	No	No
9	00001001	0	Yes	No	No	Yes
10	00001010	0	Yes	No	Yes	No
11	00001011	0	Yes	No	Yes	Yes
12	00001100	0	Yes	Yes	No	No
13	00001101	0	Yes	Yes	No	Yes
14	00001110	0	Yes	Yes	Yes	No
15	00001111	0	Yes	Yes	Yes	Yes
16	00010000	1	No	No	No	No
17	00010001	1	No	No	No	Yes
18	00010010	1	No	No	Yes	No
19	00010011	1	No	No	Yes	Yes
20	00010100	1	No	Yes	No	No
21	00010101	1	No	Yes	No	Yes
22	00010110	1	No	Yes	Yes	No
23	00010111	1	No	Yes	Yes	Yes
24	00011000	1	Yes	No	No	No
25	00011001	1	Yes	No	No	Yes
26	00011010	1	Yes	No	Yes	No
27	00011011	1	Yes	No	Yes	Yes

Table 26. State number (decimal and binary) representations and their associated education and training-related characteristics (for results over all industries).
***Table continued on next page**

State Number (Decimal)	Binary Value	EDUC (code Number)	CLASSTRAIN?	JOBTRAIN?	HELPTRAIN?	NOHELPTRAIN?
28	00011100	1	Yes	Yes	No	No
29	00011101	1	Yes	Yes	No	Yes
30	00011110	1	Yes	Yes	Yes	No
31	00011111	1	Yes	Yes	Yes	Yes
32	00100000	2	No	No	No	No
33	00100001	2	No	No	No	Yes
34	00100010	2	No	No	Yes	No
35	00100011	2	No	No	Yes	Yes
36	00100100	2	No	Yes	No	No
37	00100101	2	No	Yes	No	Yes
38	00100110	2	No	Yes	Yes	No
39	00100111	2	No	Yes	Yes	Yes
40	00101000	2	Yes	No	No	No
41	00101001	2	Yes	No	No	Yes
42	00101010	2	Yes	No	Yes	No
43	00101011	2	Yes	No	Yes	Yes
44	00101100	2	Yes	Yes	No	No
45	00101101	2	Yes	Yes	No	Yes
46	00101110	2	Yes	Yes	Yes	No
47	00101111	2	Yes	Yes	Yes	Yes
48	00110000	3	No	No	No	No
49	00110001	3	No	No	No	Yes
50	00110010	3	No	No	Yes	No
51	00110011	3	No	No	Yes	Yes
52	00110100	3	No	Yes	No	No
53	00110101	3	No	Yes	No	Yes
54	00110110	3	No	Yes	Yes	No
55	00110111	3	No	Yes	Yes	Yes
56	00111000	3	Yes	No	No	No
57	00111001	3	Yes	No	No	Yes
58	00111010	3	Yes	No	Yes	No
59	00111011	3	Yes	No	Yes	Yes
60	00111100	3	Yes	Yes	No	No
61	00111101	3	Yes	Yes	No	Yes
62	00111110	3	Yes	Yes	Yes	No
63	00111111	3	Yes	Yes	Yes	Yes
64	01000000	4	No	No	No	No
65	01000001	4	No	No	No	Yes
66	01000010	4	No	No	Yes	No

Table 26 (continued). State number (decimal and binary) representations and their associated education and training-related characteristics (for results over all industries).
***Table continued on next page**

State Number (Decimal)	Binary Value	EDUC (code Number)	CLASSTRAIN?	JOBTRAIN?	HELPTRAIN?	NOHELPTRAIN?
67	01000011	4	No	No	Yes	Yes
68	01000100	4	No	Yes	No	No
69	01000101	4	No	Yes	No	Yes
70	01000110	4	No	Yes	Yes	No
71	01000111	4	No	Yes	Yes	Yes
72	01001000	4	Yes	No	No	No
73	01001001	4	Yes	No	No	Yes
74	01001010	4	Yes	No	Yes	No
75	01001011	4	Yes	No	Yes	Yes
76	01001100	4	Yes	Yes	No	No
77	01001101	4	Yes	Yes	No	Yes
78	01001110	4	Yes	Yes	Yes	No
79	01001111	4	Yes	Yes	Yes	Yes
80	01010000	5	No	No	No	No
81	01010001	5	No	No	No	Yes
82	01010010	5	No	No	Yes	No
83	01010011	5	No	No	Yes	Yes
84	01010100	5	No	Yes	No	No
85	01010101	5	No	Yes	No	Yes
86	01010110	5	No	Yes	Yes	No
87	01010111	5	No	Yes	Yes	Yes
88	01011000	5	Yes	No	No	No
89	01011001	5	Yes	No	No	Yes
90	01011010	5	Yes	No	Yes	No
91	01011011	5	Yes	No	Yes	Yes
92	01011100	5	Yes	Yes	No	No
93	01011101	5	Yes	Yes	No	Yes
94	01011110	5	Yes	Yes	Yes	No
95	01011111	5	Yes	Yes	Yes	Yes
96	01110000	6	No	No	No	No
97	01110001	6	No	No	No	Yes
98	01110010	6	No	No	Yes	No
99	01110011	6	No	No	Yes	Yes
100	01110100	6	No	Yes	No	No
101	01110101	6	No	Yes	No	Yes
102	01110110	6	No	Yes	Yes	No
103	01110111	6	No	Yes	Yes	Yes
104	01111000	6	Yes	No	No	No
105	01111001	6	Yes	No	No	Yes

Table 26 (continued). State number (decimal and binary) representations and their associated education and training-related characteristics (for results over all industries).

***Table continued on next page.**

State Number (Decimal)	Binary Value	EDUC (code Number)	CLASSTRAIN?	JOBTRAIN?	HELPTRAIN?	NOHELPTRAIN?
106	01111010	6	Yes	No	Yes	No
107	01111011	6	Yes	No	Yes	Yes
108	01111100	6	Yes	Yes	No	No
109	01111101	6	Yes	Yes	No	Yes
110	01111110	6	Yes	Yes	Yes	No
111	01111111	6	Yes	Yes	Yes	Yes
112	10000000	7	No	No	No	No
113	10000001	7	No	No	No	Yes
114	10000010	7	No	No	Yes	No
115	10000011	7	No	No	Yes	Yes
116	10000100	7	No	Yes	No	No
117	10000101	7	No	Yes	No	Yes
118	10000110	7	No	Yes	Yes	No
119	10000111	7	No	Yes	Yes	Yes
120	10001000	7	Yes	No	No	No
121	10001001	7	Yes	No	No	Yes
122	10001010	7	Yes	No	Yes	No
123	10001011	7	Yes	No	Yes	Yes
124	10001100	7	Yes	Yes	No	No
125	10001101	7	Yes	Yes	No	Yes
126	10001110	7	Yes	Yes	Yes	No
127	10001111	7	Yes	Yes	Yes	Yes
128	10010000	8	No	No	No	No
129	10010001	8	No	No	No	Yes
130	10010010	8	No	No	Yes	No
131	10010011	8	No	No	Yes	Yes
132	10010100	8	No	Yes	No	No
133	10010101	8	No	Yes	No	Yes
134	10010110	8	No	Yes	Yes	No
135	10010111	8	No	Yes	Yes	Yes
136	10011000	8	Yes	No	No	No
137	10011001	8	Yes	No	No	Yes
138	10011010	8	Yes	No	Yes	No
139	10011011	8	Yes	No	Yes	Yes
140	10011100	8	Yes	Yes	No	No
141	10011101	8	Yes	Yes	No	Yes
142	10011110	8	Yes	Yes	Yes	No
143	10011111	8	Yes	Yes	Yes	Yes
144	10100000	9	No	No	No	No
145	10100001	9	No	No	No	Yes

Table 26 (continued). State number (decimal and binary) representations and their associated education and training-related characteristics (for results over all industries).
***Table continued on next page.**

State Number (Decimal)	Binary Value	EDUC (code Number)	CLASSTRAIN?	JOBTRAIN?	HELPTRAIN?	NOHELPTRAIN?
146	10100010	9	No	No	Yes	No
147	10100011	9	No	No	Yes	Yes
148	10100100	9	No	Yes	No	No
149	10100101	9	No	Yes	No	Yes
150	10100110	9	No	Yes	Yes	No
151	10100111	9	No	Yes	Yes	Yes
152	10101000	9	Yes	No	No	No
153	10101001	9	Yes	No	No	Yes
154	10101010	9	Yes	No	Yes	No
155	10101011	9	Yes	No	Yes	Yes
156	10101100	9	Yes	Yes	No	No
157	10101101	9	Yes	Yes	No	Yes
158	10101110	9	Yes	Yes	Yes	No
159	10101111	9	Yes	Yes	Yes	Yes

Table 26 (continued). State number (decimal and binary) representations and their associated education and training-related characteristics (for results over all industries).

In reference to Table 27, for profit growth, we see a transition from 100 (01100100) to 6 (00000110). This corresponds to starting with [employees with a college diploma and receiving on-the-job training], change to uneducated employees, then add employer-aided non-work-related training. This suggests that an employee with a college diploma with on-the-job training is likely to be part of a failing company, whereas an employee with no education but receives on-the-job training and receives help for training not directly related to his/her job is generally part of a growing company. So a company would be advised to seek less educated employees in general. This means that training an employee is the better form of education than formal education, when maximizing performance. For labor productivity growth, we see a transition from 149 (10010101) to 137 (10001001). This corresponds to starting with [graduate degree earning employees with on-the-job training, and employer training for work w/o aid from employer], change to employees with a university professional accreditation, remove on-the-job training, and add classroom training. This suggests that an employee with a graduate degree that receives on-the-job training and receives training related to work without aid is generally part of a failing company. Conversely, an employee with a university professional accreditation along with formal training and training related to work without aid is generally part of a growing company in terms of labor productivity. Thus, a company would be recommended to seek out individuals who have a university professional accreditation.

For profit margin we see a transition from 41 (00111101) to 63 (00111111). This corresponds to starting with [employees with some secondary school education, classroom training, and training for work w/o aid from employer], change to employees with secondary school diplomas, add employer-aided non-work-related training, and add on-the-job training. This suggests that an employee with a secondary education that receives lots of training (but not unrelated training) is generally associated with a failing company. Conversely, the same educated job position with all the training (including unrelated training) is generally part of a thriving company in terms of productivity. For labor productivity, we see a transition from 37 (00100101) to 78 (01001110). This corresponds to starting with [employees with some secondary school education, on-the-job training, and training for work w/o aid from employer], change employees to uneducated, add classroom training, change employees to some postsecondary education, remove training for work w/o aid from employer, and remove classroom training. This suggests that employees that work in a position requiring some secondary education along with on-the-job training and unaided outside training are generally part of a failing company. On the other hand, an employee with some postsecondary education and all the training except outside, unaided training related to the job, is generally part of a thriving company.

Overall, the results are mixed. It appears that on-the-job training is very important. This is a reasonable result given that most jobs that require training on-site are directly related to the job function of the employee and thus will affect firm performance.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	100	-1197.47	6	7708.23	100-4-6
glprod	% change per employee	149	-0.503187	137	6.660355	149-133-129-137
profit	$ per employee	41	-0.055546	63	5.5754102	41-57-59-63
lprod	$ per employee	37	63579.61	78	938499.98	37-5-13-77-76-78

Table 27. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (Education and Training).

6 Computer Use and Human Resource Management Practices

The binary order of the computer use and human resource management practices (both previously described) variables discussed in this section are as follows: **COMPUSE, TECHUSE, HRM1, HRM2, HRM3, HRM4, HRM5, HRM6.** They were analyzed together to discover which organizational decisions in regards to the two areas leads to optimal firm performance. The associated state numbers used in the following discussion relates to the characteristics described in Table 28.

State Number (Decimal)	**Binary Value**	**COMPUSE?**	**TECHUSE?**	**HRM1?**	**HRM2?**	**HRM3?**	**HRM4?**	**HRM5?**	**HRM6?**
0	00000000	No	No	No	No	No	No	No	No
1	00000001	No	No	No	No	No	No	No	Yes
2	00000010	No	No	No	No	No	No	Yes	No
3	00000011	No	No	No	No	No	No	Yes	Yes
4	00000100	No	No	No	No	No	Yes	No	No
5	00000101	No	No	No	No	No	Yes	No	Yes
6	00000110	No	No	No	No	No	Yes	Yes	No
7	00000111	No	No	No	No	No	Yes	Yes	Yes
8	00001000	No	No	No	No	Yes	No	No	No
9	00001001	No	No	No	No	Yes	No	No	Yes
10	00001010	No	No	No	No	Yes	No	Yes	No
11	00001011	No	No	No	No	Yes	No	Yes	Yes
12	00001100	No	No	No	No	Yes	Yes	No	No
13	00001101	No	No	No	No	Yes	Yes	No	Yes
14	00001110	No	No	No	No	Yes	Yes	Yes	No
15	00001111	No	No	No	No	Yes	Yes	Yes	Yes
16	00010000	No	No	No	Yes	No	No	No	No
17	00010001	No	No	No	Yes	No	No	No	Yes
18	00010010	No	No	No	Yes	No	No	Yes	No
19	00010011	No	No	No	Yes	No	No	Yes	Yes
20	00010100	No	No	No	Yes	No	Yes	No	No
21	00010101	No	No	No	Yes	No	Yes	No	Yes
22	00010110	No	No	No	Yes	No	Yes	Yes	No
23	00010111	No	No	No	Yes	No	Yes	Yes	Yes
24	00011000	No	No	No	Yes	Yes	No	No	No
25	00011001	No	No	No	Yes	Yes	No	No	Yes
26	00011010	No	No	No	Yes	Yes	No	Yes	No
27	00011011	No	No	No	Yes	Yes	No	Yes	Yes
28	00011100	No	No	No	Yes	Yes	Yes	No	No
29	00011101	No	No	No	Yes	Yes	Yes	No	Yes
30	00011110	No	No	No	Yes	Yes	Yes	Yes	No
31	00011111	No	No	No	Yes	Yes	Yes	Yes	Yes
32	00100000	No	No	Yes	No	No	No	No	No
33	00100001	No	No	Yes	No	No	No	No	Yes
34	00100010	No	No	Yes	No	No	No	Yes	No
35	00100011	No	No	Yes	No	No	No	Yes	Yes

Table 28. State number (decimal and binary) representations and their associated computer use and HRM-related characteristics (for results over all industries).
***Table continues on next page**

State Number (Decimal)	Binary Value	COMPUSE?	TECHUSE?	HRM1?	HRM2?	HRM3?	HRM4?	HRM5?	HRM6?
36	00100100	No	No	Yes	No	No	Yes	No	No
37	00100101	No	No	Yes	No	No	Yes	No	Yes
38	00100110	No	No	Yes	No	No	Yes	Yes	No
39	00100111	No	No	Yes	No	No	Yes	Yes	Yes
40	00101000	No	No	Yes	No	Yes	No	No	No
41	00101001	No	No	Yes	No	Yes	No	No	Yes
42	00101010	No	No	Yes	No	Yes	No	Yes	No
43	00101011	No	No	Yes	No	Yes	No	Yes	Yes
44	00101100	No	No	Yes	No	Yes	Yes	No	No
45	00101101	No	No	Yes	No	Yes	Yes	No	Yes
46	00101110	No	No	Yes	No	Yes	Yes	Yes	No
47	00101111	No	No	Yes	No	Yes	Yes	Yes	Yes
48	00110000	No	No	Yes	Yes	No	No	No	No
49	00110001	No	No	Yes	Yes	No	No	No	Yes
50	00110010	No	No	Yes	Yes	No	No	Yes	No
51	00110011	No	No	Yes	Yes	No	No	Yes	Yes
52	00110100	No	No	Yes	Yes	No	Yes	No	No
53	00110101	No	No	Yes	Yes	No	Yes	No	Yes
54	00110110	No	No	Yes	Yes	No	Yes	Yes	No
55	00110111	No	No	Yes	Yes	No	Yes	Yes	Yes
56	00111000	No	No	Yes	Yes	Yes	No	No	No
57	00111001	No	No	Yes	Yes	Yes	No	No	Yes
58	00111010	No	No	Yes	Yes	Yes	No	Yes	No
59	00111011	No	No	Yes	Yes	Yes	No	Yes	Yes
60	00111100	No	No	Yes	Yes	Yes	Yes	No	No
61	00111101	No	No	Yes	Yes	Yes	Yes	No	Yes
62	00111110	No	No	Yes	Yes	Yes	Yes	Yes	No
63	00111111	No	No	Yes	Yes	Yes	Yes	Yes	Yes
64	01000000	No	Yes	No	No	No	No	No	No
65	01000001	No	Yes	No	No	No	No	No	Yes
66	01000010	No	Yes	No	No	No	No	Yes	No
67	01000011	No	Yes	No	No	No	No	Yes	Yes
68	01000100	No	Yes	No	No	No	Yes	No	No
69	01000101	No	Yes	No	No	No	Yes	No	Yes
70	01000110	No	Yes	No	No	No	Yes	Yes	No
71	01000111	No	Yes	No	No	No	Yes	Yes	Yes
72	01001000	No	Yes	No	No	Yes	No	No	No
73	01001001	No	Yes	No	No	Yes	No	No	Yes

Table 28 (continued). State number (decimal and binary) representations and their associated computer use and HRM-related characteristics (for results over all industries).
***Table continues on next page**

State Number (Decimal)	Binary Value	COMPUSE?	TECHUSE?	HRM1?	HRM2?	HRM3?	HRM4?	HRM5?	HRM6?
74	01001010	No	Yes	No	No	Yes	No	Yes	No
75	01001011	No	Yes	No	No	Yes	No	Yes	Yes
76	01001100	No	Yes	No	No	Yes	Yes	No	No
77	01001101	No	Yes	No	No	Yes	Yes	No	Yes
78	01001110	No	Yes	No	No	Yes	Yes	Yes	No
79	01001111	No	Yes	No	No	Yes	Yes	Yes	Yes
80	01010000	No	Yes	No	Yes	No	No	No	No
81	01010001	No	Yes	No	Yes	No	No	No	Yes
82	01010010	No	Yes	No	Yes	No	No	Yes	No
83	01010011	No	Yes	No	Yes	No	No	Yes	Yes
84	01010100	No	Yes	No	Yes	No	Yes	No	No
85	01010101	No	Yes	No	Yes	No	Yes	No	Yes
86	01010110	No	Yes	No	Yes	No	Yes	Yes	No
87	01010111	No	Yes	No	Yes	No	Yes	Yes	Yes
88	01011000	No	Yes	No	Yes	Yes	No	No	No
89	01011001	No	Yes	No	Yes	Yes	No	No	Yes
90	01011010	No	Yes	No	Yes	Yes	No	Yes	No
91	01011011	No	Yes	No	Yes	Yes	No	Yes	Yes
92	01011100	No	Yes	No	Yes	Yes	Yes	No	No
93	01011101	No	Yes	No	Yes	Yes	Yes	No	Yes
94	01011110	No	Yes	No	Yes	Yes	Yes	Yes	No
95	01011111	No	Yes	No	Yes	Yes	Yes	Yes	Yes
96	01100000	No	Yes	Yes	No	No	No	No	No
97	01100001	No	Yes	Yes	No	No	No	No	Yes
98	01100010	No	Yes	Yes	No	No	No	Yes	No
99	01100011	No	Yes	Yes	No	No	No	Yes	Yes
100	01100100	No	Yes	Yes	No	No	Yes	No	No
101	01100101	No	Yes	Yes	No	No	Yes	No	Yes
102	01100110	No	Yes	Yes	No	No	Yes	Yes	No
103	01100111	No	Yes	Yes	No	No	Yes	Yes	Yes
104	01101000	No	Yes	Yes	No	Yes	No	No	No
105	01101001	No	Yes	Yes	No	Yes	No	No	Yes
106	01101010	No	Yes	Yes	No	Yes	No	Yes	No
107	01101011	No	Yes	Yes	No	Yes	No	Yes	Yes
108	01101100	No	Yes	Yes	No	Yes	Yes	No	No
109	01101101	No	Yes	Yes	No	Yes	Yes	No	Yes
110	01101110	No	Yes	Yes	No	Yes	Yes	Yes	No
111	01101111	No	Yes	Yes	No	Yes	Yes	Yes	Yes
112	01110000	No	Yes	Yes	Yes	No	No	No	No
113	01110001	No	Yes	Yes	Yes	No	No	No	Yes

Table 28 (continued). State number (decimal and binary) representations and their associated computer use and HRM-related characteristics (for results over all industries).
***Table continues on next page**

State Number (Decimal)	**Binary Value**	**COMPUSE?**	**TECHUSE?**	**HRM1?**	**HRM2?**	**HRM3?**	**HRM4?**	**HRM5?**	**HRM6?**
114	01110010	No	Yes	Yes	Yes	No	No	Yes	No
115	01110011	No	Yes	Yes	Yes	No	No	Yes	Yes
116	01110100	No	Yes	Yes	Yes	No	Yes	No	No
117	01110101	No	Yes	Yes	Yes	No	Yes	No	Yes
118	01110110	No	Yes	Yes	Yes	No	Yes	Yes	No
119	01110111	No	Yes	Yes	Yes	No	Yes	Yes	Yes
120	01111000	No	Yes	Yes	Yes	Yes	No	No	No
121	01111001	No	Yes	Yes	Yes	Yes	No	No	Yes
122	01111010	No	Yes	Yes	Yes	Yes	No	Yes	No
123	01111011	No	Yes	Yes	Yes	Yes	No	Yes	Yes
124	01111100	No	Yes	Yes	Yes	Yes	Yes	No	No
125	01111101	No	Yes	Yes	Yes	Yes	Yes	No	Yes
126	01111110	No	Yes	Yes	Yes	Yes	Yes	Yes	No
127	01111111	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
128	10000000	Yes	No	No	No	No	No	No	No
129	10000001	Yes	No	No	No	No	No	No	Yes
130	10000010	Yes	No	No	No	No	No	Yes	No
131	10000011	Yes	No	No	No	No	No	Yes	Yes
132	10000100	Yes	No	No	No	No	Yes	No	No
133	10000101	Yes	No	No	No	No	Yes	No	Yes
134	10000110	Yes	No	No	No	No	Yes	Yes	No
135	10000111	Yes	No	No	No	No	Yes	Yes	Yes
136	10001000	Yes	No	No	No	Yes	No	No	No
137	10001001	Yes	No	No	No	Yes	No	No	Yes
138	10001010	Yes	No	No	No	Yes	No	Yes	No
139	10001011	Yes	No	No	No	Yes	No	Yes	Yes
140	10001100	Yes	No	No	No	Yes	Yes	No	No
141	10001101	Yes	No	No	No	Yes	Yes	No	Yes
142	10001110	Yes	No	No	No	Yes	Yes	Yes	No
143	10001111	Yes	No	No	No	Yes	Yes	Yes	Yes
144	10010000	Yes	No	No	Yes	No	No	No	No
145	10010001	Yes	No	No	Yes	No	No	No	Yes
146	10010010	Yes	No	No	Yes	No	No	Yes	No
147	10010011	Yes	No	No	Yes	No	No	Yes	Yes
148	10010100	Yes	No	No	Yes	No	Yes	No	No
149	10010101	Yes	No	No	Yes	No	Yes	No	Yes
150	10010110	Yes	No	No	Yes	No	Yes	Yes	No
151	10010111	Yes	No	No	Yes	No	Yes	Yes	Yes
152	10011000	Yes	No	No	Yes	Yes	No	No	No
153	10011001	Yes	No	No	Yes	Yes	No	No	Yes

Table 28 (continued). State number (decimal and binary) representations and their associated computer use and HRM-related characteristics (for results over all industries).
***Table continues on next page**

State Number (Decimal)	Binary Value	COMPUSE?	TECHUSE?	HRM1?	HRM2?	HRM3?	HRM4?	HRM5?	HRM6?
154	10011010	Yes	No	No	Yes	Yes	No	Yes	No
155	10011011	Yes	No	No	Yes	Yes	No	Yes	Yes
156	10011100	Yes	No	No	Yes	Yes	Yes	No	No
157	10011101	Yes	No	No	Yes	Yes	Yes	No	Yes
158	10011110	Yes	No	No	Yes	Yes	Yes	Yes	No
159	10011111	Yes	No	No	Yes	Yes	Yes	Yes	Yes
160	10100000	Yes	No	Yes	No	No	No	No	No
161	10100001	Yes	No	Yes	No	No	No	No	Yes
162	10100010	Yes	No	Yes	No	No	No	Yes	No
163	10100011	Yes	No	Yes	No	No	No	Yes	Yes
164	10100100	Yes	No	Yes	No	No	Yes	No	No
165	10100101	Yes	No	Yes	No	No	Yes	No	Yes
166	10100110	Yes	No	Yes	No	No	Yes	Yes	No
167	10100111	Yes	No	Yes	No	No	Yes	Yes	Yes
168	10101000	Yes	No	Yes	No	Yes	No	No	No
169	10101001	Yes	No	Yes	No	Yes	No	No	Yes
170	10101010	Yes	No	Yes	No	Yes	No	Yes	No
171	10101011	Yes	No	Yes	No	Yes	No	Yes	Yes
172	10101100	Yes	No	Yes	No	Yes	Yes	No	No
173	10101101	Yes	No	Yes	No	Yes	Yes	No	Yes
174	10101110	Yes	No	Yes	No	Yes	Yes	Yes	No
175	10101111	Yes	No	Yes	No	Yes	Yes	Yes	Yes
176	10110000	Yes	No	Yes	Yes	No	No	No	No
177	10110001	Yes	No	Yes	Yes	No	No	No	Yes
178	10110010	Yes	No	Yes	Yes	No	No	Yes	No
179	10110011	Yes	No	Yes	Yes	No	No	Yes	Yes
180	10110100	Yes	No	Yes	Yes	No	Yes	No	No
181	10110101	Yes	No	Yes	Yes	No	Yes	No	Yes
182	10110110	Yes	No	Yes	Yes	No	Yes	Yes	No
183	10110111	Yes	No	Yes	Yes	No	Yes	Yes	Yes
184	10111000	Yes	No	Yes	Yes	Yes	No	No	No
185	10111001	Yes	No	Yes	Yes	Yes	No	No	Yes
186	10111010	Yes	No	Yes	Yes	Yes	No	Yes	No
187	10111011	Yes	No	Yes	Yes	Yes	No	Yes	Yes
188	10111100	Yes	No	Yes	Yes	Yes	Yes	No	No
189	10111101	Yes	No	Yes	Yes	Yes	Yes	No	Yes
190	10111110	Yes	No	Yes	Yes	Yes	Yes	Yes	No
191	10111111	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
192	11000000	Yes	Yes	No	No	No	No	No	No
193	11000001	Yes	Yes	No	No	No	No	No	Yes

Table 28 (continued). State number (decimal and binary) representations and their associated computer use and HRM-related characteristics (for results over all industries).
***Table continues on next page**

State Number (Decimal)	Binary Value	COMPUSE?	TECHUSE?	HRM1?	HRM2?	HRM3?	HRM4?	HRM5?	HRM6?
194	11000010	Yes	Yes	No	No	No	No	Yes	No
195	11000011	Yes	Yes	No	No	No	No	Yes	Yes
196	11000100	Yes	Yes	No	No	No	Yes	No	No
197	11000101	Yes	Yes	No	No	No	Yes	No	Yes
198	11000110	Yes	Yes	No	No	No	Yes	Yes	No
199	11000111	Yes	Yes	No	No	No	Yes	Yes	Yes
200	11001000	Yes	Yes	No	No	Yes	No	No	No
201	11001001	Yes	Yes	No	No	Yes	No	No	Yes
202	11001010	Yes	Yes	No	No	Yes	No	Yes	No
203	11001011	Yes	Yes	No	No	Yes	No	Yes	Yes
204	11001100	Yes	Yes	No	No	Yes	Yes	No	No
205	11001101	Yes	Yes	No	No	Yes	Yes	No	Yes
206	11001110	Yes	Yes	No	No	Yes	Yes	Yes	No
207	11001111	Yes	Yes	No	No	Yes	Yes	Yes	Yes
208	11010000	Yes	Yes	No	Yes	No	No	No	No
209	11010001	Yes	Yes	No	Yes	No	No	No	Yes
210	11010010	Yes	Yes	No	Yes	No	No	Yes	No
211	11010011	Yes	Yes	No	Yes	No	No	Yes	Yes
212	11010100	Yes	Yes	No	Yes	No	Yes	No	No
213	11010101	Yes	Yes	No	Yes	No	Yes	No	Yes
214	11010110	Yes	Yes	No	Yes	No	Yes	Yes	No
215	11010111	Yes	Yes	No	Yes	No	Yes	Yes	Yes
216	11011000	Yes	Yes	No	Yes	Yes	No	No	No
217	11011001	Yes	Yes	No	Yes	Yes	No	No	Yes
218	11011010	Yes	Yes	No	Yes	Yes	No	Yes	No
219	11011011	Yes	Yes	No	Yes	Yes	No	Yes	Yes
220	11011100	Yes	Yes	No	Yes	Yes	Yes	No	No
221	11011101	Yes	Yes	No	Yes	Yes	Yes	No	Yes
222	11011110	Yes	Yes	No	Yes	Yes	Yes	Yes	No
223	11011111	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
224	11100000	Yes	Yes	Yes	No	No	No	No	No
225	11100001	Yes	Yes	Yes	No	No	No	No	Yes
226	11100010	Yes	Yes	Yes	No	No	No	Yes	No
227	11100011	Yes	Yes	Yes	No	No	No	Yes	Yes
228	11100100	Yes	Yes	Yes	No	No	Yes	No	No
229	11100101	Yes	Yes	Yes	No	No	Yes	No	Yes
230	11100110	Yes	Yes	Yes	No	No	Yes	Yes	No
231	11100111	Yes	Yes	Yes	No	No	Yes	Yes	Yes
232	11101000	Yes	Yes	Yes	No	Yes	No	No	No
233	11101001	Yes	Yes	Yes	No	Yes	No	No	Yes

Table 28 (continued). State number (decimal and binary) representations and their associated computer use and HRM-related characteristics (for results over all industries).
***Table continues on next page**

State Number (Decimal)	**Binary Value**	**COMPUSE?**	**TECHUSE?**	**HRM1?**	**HRM2?**	**HRM3?**	**HRM4?**	**HRM5?**	**HRM6?**
234	11101010	Yes	Yes	Yes	No	Yes	No	Yes	No
235	11101011	Yes	Yes	Yes	No	Yes	No	Yes	Yes
236	11101100	Yes	Yes	Yes	No	Yes	Yes	No	No
237	11101101	Yes	Yes	Yes	No	Yes	Yes	No	Yes
238	11101110	Yes	Yes	Yes	No	Yes	Yes	Yes	No
239	11101111	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
240	11110000	Yes	Yes	Yes	Yes	No	No	No	No
241	11110001	Yes	Yes	Yes	Yes	No	No	No	Yes
242	11110010	Yes	Yes	Yes	Yes	No	No	Yes	No
243	11110011	Yes	Yes	Yes	Yes	No	No	Yes	Yes
244	11110100	Yes	Yes	Yes	Yes	No	Yes	No	No
245	11110101	Yes	Yes	Yes	Yes	No	Yes	No	Yes
246	11110110	Yes	Yes	Yes	Yes	No	Yes	Yes	No
247	11110111	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
248	11111000	Yes	Yes	Yes	Yes	Yes	No	No	No
249	11111001	Yes	Yes	Yes	Yes	Yes	No	No	Yes
250	11111010	Yes	Yes	Yes	Yes	Yes	No	Yes	No
251	11111011	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
252	11111100	Yes	Yes	Yes	Yes	Yes	Yes	No	No
253	11111101	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
254	11111110	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
255	11111111	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 28 (continued). State number (decimal and binary) representations and their associated computer use and HRM-related characteristics (for results over all industries).

In reference to Table 29, for profit growth, we see a transition from state 130 (10000010) to state 171 (10101011). This corresponds to starting with [employee computer use and joint labor-management committees], adding self-directed work groups, adding information sharing with employees, and adding an employee suggestion program. This suggests that a company that has an employee that uses a computer and uses joint labor-management committees should also employ a an employee suggestion program, information sharing, and self-directed work groups to optimize profit growth. For labor productivity growth, we see a transition from 223 (11011111) to 255

(11111111). This corresponds to starting with [employee computer use, employee use of computer controlled/assisted technology, flexible job design, information sharing with employees, problem solving teams, joint labor-management committees, self-directed work groups] and simply adding and employee suggestion program. This recommends that companies should have employees that use computers and computer-related technologies and all human resource management practices should be employed as well. Flexible job design appears to be a key component to this equation since without it, growth reverses.

For profit margin we see a transition from 25 (00011001) to 73 (01001001). This corresponds to starting with [flexible job design, information sharing with employees, self-directed work groups], removing flexible job design, and adding employee use of computer controlled/assisted technology. This suggests that computer controlled/assisted technology, information sharing, and self-directed work groups are vital for productivity. For labor productivity, we see a transition from 93 (01011101) to 146 (10010010). This corresponds to starting with [employee use of computer controlled/assisted technology, flexible job design, information sharing with employees, problem solving teams, self-directed work groups], removing employee use of computer controlled/assisted technology, adding employee computer use, removing problem solving teams, removing directed work groups, adding joint labor-management committees, and removing information sharing with employees. This suggests that employee computer use, joint labor-management committees, and flexible job design are important for a firm.

Overall, some form of technology use and human resources management practices should be employed, but it depends on the desired objective. This partially coincides with previous studies in that HRM is a necessary implementation along with a company that employees innovative new technologies, but in a weak sense.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	130	-2135.36	171	744.86043	130-131-139-171
glprod	% change per employee	223	-0.703601	255	11.536082	223-255
profit	$ per employee	25	-0.224475	73	7.4314578	25-9-73
lprod	$ per employee	93	62048.88	146	1091578.6	93-29-157-153-152-154-146

Table 29. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (Computer Use and Human Resource Management Practices).

As this is the largest graph that is examined using the survey dataset, computation times were examined for the four problems as shown in Table 30. As you can see this is still a fairly simple problem for the algorithms to solve even though there are 256 vertices in the graph. However, recall that there are only 8 organizational practices being considered and one constraint. A firm could quite possibly want to consider many more organizational practices while considering several more constraints.

The results are similar to those from our results in Section 5.1 (Table 12). The CSPP method at least equals and often times outperforms the other methods for both optimal and near-optimal solution specifications.

	Run Time (secs) - 100% opt.			Run Time (secs) - 95% opt.		
Perfromance Variable	D&B	CRW	CSPP	D&B	CRW	CSPP
gprofit	0.03	0.01	0.01	0.01	0.01	0.00
glprod	0.02	0.00	0.00	0.02	0.00	0.00
profit	0.03	0.02	0.02	0.02	0.01	0.00
lprod	0.05	0.03	0.02	0.03	0.02	0.01

Table 30. Runs times of the CSPP, CRW, and D&B algorithms for the four performance variables as shown from Table 43 using Matlab (Computer Use and Human Resource Management Practices).

Overall Conclusion

Collectively, we've seen that the choice of performance measure generally makes a significant difference on which operational states are optimal and/or weakest. This presents a dilemma for managers who'd like to be confident that their future management strategies result in adequate profitability and productivity, as well as future growth of these measures.

Often there are times when budget constraints are restrictive to a particular company and these results show that sub-optimal solutions are required. Since strategies change depending on performance measures, managers that don't have preferences towards one specific measure could potentially add in extra restrictive constraints, such as limits to overall implementation costs, to narrow down their final strategic choices.

In terms of previous economic results, there is some evidence that a firm that combines organizational practices to support new innovations and technologies performs well, but it is not overwhelming. There appears to be many unique paths to obtain high performance depending on the performance measure used.

5.2.2 Industry-Level Results

Running the CSPP algorithm over the industry-level data, we determined the shortest paths starting from the lowest performing state to the highest performing state that was attainable given the technology budget constraint. The budget constraint was set at the yearly industry average. This constraint value was chosen in order to ensure it would be periodically violated while running the algorithm, thus producing non-trivial solutions. These violations can result in a maximum-valued state not being attainable, as can be seen in some of the results. The state variables were ordered in the following way:

TECH1, TECH23, TTL_EMPBI, PROCPROD, & TRNG_EXPBI.

Each of the variables answered a yes/no question, specifically:

TECH1: Did the workplace implement new hardware/software this year?

TECH23: Did the workplace implement other technologies this year?

TTL_EMPBI: Was the total number of employees higher than industry average?

PROCPROD: Was a new product or process innovation introduced?

TRNG_EXPBI: Is the average training expenditure per employee higher than the industry average?

In order to better understand the state numbers' (represented in both decimal and binary formats) characteristics in the following sections, refer to Table 31.

State Number (Decimal)	**Binary Value**	**New Hardware or Software?**	**Other New Technology?**	**# of Employees: Above / Below Industry Average?**	**New Product or Process Innovation?**	**Training Expenditure Per Employee: Above /Below Industry Average?**
0	00000	No	No	Below	No	No
1	00001	No	No	Below	No	Yes
2	00010	No	No	Below	Yes	No
3	00011	No	No	Below	Yes	Yes
4	00100	No	No	Above	No	No
5	00101	No	No	Above	No	Yes
6	00110	No	No	Above	Yes	No
7	00111	No	No	Above	Yes	Yes
8	01000	No	Yes	Below	No	No
9	01001	No	Yes	Below	No	Yes
10	01010	No	Yes	Below	Yes	No
11	01011	No	Yes	Below	Yes	Yes
12	01100	No	Yes	Above	No	No
13	01101	No	Yes	Above	No	Yes
14	01110	No	Yes	Above	Yes	No
15	01111	No	Yes	Above	Yes	Yes
16	10000	Yes	No	Below	No	No
17	10001	Yes	No	Below	No	Yes
18	10010	Yes	No	Below	Yes	No
19	10011	Yes	No	Below	Yes	Yes
20	10100	Yes	No	Above	No	No
21	10101	Yes	No	Above	No	Yes
22	10110	Yes	No	Above	Yes	No
23	10111	Yes	No	Above	Yes	Yes
24	11000	Yes	Yes	Below	No	No
25	11001	Yes	Yes	Below	No	Yes
26	11010	Yes	Yes	Below	Yes	No
27	11011	Yes	Yes	Below	Yes	Yes
28	11100	Yes	Yes	Above	No	No
29	11101	Yes	Yes	Above	No	Yes
30	11110	Yes	Yes	Above	Yes	No
31	11111	Yes	Yes	Above	Yes	Yes

Table 31. State number (decimal and binary) representations and their associated characteristics (for industry level results).

1 Forestry, Mining, Oil, and Gas Extraction

In regards to forestry, mining, oil, and gas extraction, Table 32 shows an industry summary of the start, minimum and maximum states as well as the maximum values and optimal paths associated with each of the performance variables profit growth (gprofit), labor productivity growth (glprod), profit, and labor productivity (lprod), respectively.

In terms of profit growth, we can see that under state 23 (10111), which represents only implementing new hardware and/or software technologies, a large workforce, creating new innovation(s), and spending an above-average amount of money on training results in poor performance for the workplace, on average. The highest state in regards to this performance variable is 17 (10001), which means no new innovations should be introduced as well as reducing employee size. However, due to the technology budget constraint, this maximum state is not feasible. Instead state 4 (00100) is the best feasible option, which focuses on keeping workforce numbers high and staying away from high levels of training and innovation. The transitions leading to maximum attainable performance involves starting with [implementing new hardware/software, large workforce, introducing a new product/process innovation, and high training expenditure], stop adding new hardware/software, stop introducing new product/process innovation, and reduce the workforce training expenditure.

State 22 (10110), which keeps training low and does not implement new technologies other than hardware/software, is the minimum state in terms of labor productivity growth. The maximum state is 1 (00001), which consists of high training, while avoiding a larger workforce and avoiding new innovations. The transitions leading to maximum attainable performance involves starting with [implementing new hardware/software, large workforce, introducing a new product/process innovation, and low training expenditure], stop adding new hardware/software, stop introducing new product/process innovation, reduce the size of the workforce, and increase the workforce training expenditure per employee.

Again, state 23 (10111) is the minimum state in terms of profit, which correlates with the corresponding growth variable. State 21 (10101) is the maximum state, which consists of new hardware/software implementation, a large workforce that is well-trained. The transitions leading to maximum attainable performance involves starting with [implementing new hardware/software, large workforce, introducing a new product/process innovation, and high training expenditure], stop adding new hardware/software, stop introducing new product/process innovation, and then implement new hardware/software.

State 30 (11110), which only keeps training expenditure low, is the minimum state in terms of labor productivity. The maximum state, 23 (10111) is not attainable for this problem, so the less costly path leads to state 1 (00001) of high training. The transitions leading to maximum attainable performance involves starting with [implementing new hardware/software, implementing other technologies, large workforce, introducing a new product/process innovation, and low training expenditure for the workforce], stop implementing new hardware/software, stop implementing other technologies, stop introducing new product/process innovation, reduce the workforce, and add to training expenditure.

Overall, we see that for this industry, the minimum performance state tends to be high levels of most of the variables, whereas the highest (and near-highest) states have fewer variables implemented. These results suggest that workplaces in this industry don't need to spend high levels of money on innovation, technology and their workforce to be successful. They can focus on a few areas at most and do very well.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	23	-1.937531	17	3.3813937	23-7-5-4*
glprod	% change per employee	22	-0.178844	1	4.5623691	22-6-4-0-1
Profit	$ per employee	23	0.0451772	21	3.4843912	23-7-5-21
Lprod	$ per employee	30	164092.6	23	6332787.6	30-14-6-4-0-1*

Table 32. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (forestry, mining, oil, and gas extraction industry).
* **max state unattainable due to budget constraint**

2 Labor Intensive Tertiary Manufacturing

Referring to labor intensive tertiary manufacturing in Table 33, for profit growth, we see a transition from 1 (00001) to 18 (10010). This corresponds to starting with [small workforce with high training expenditure], reducing training expenditure, and then adding a new innovation, and then implementing new hardware/software. This transition is from one low level amount of implementation (high training only) to another relatively low level (hardware/software implementation and innovation) due to the infeasibility of reaching the maximum state, which involves implementing all variables to their optimum levels. For labor productivity growth, we see a transition from 20 (10100) to 1 (00001).

This corresponds to starting with [implementing new hardware/software, large workforce with low training expenditure], stop adding new hardware/software, reduce the size of the workforce, then increase training expenditure. The transition is from a low level of operations to even lower, cutting out computer use and downsizing, yet increasing workforce training.

For profit we see a transition from 18 (10010) to 20 (10100). This corresponds to starting with [implementing new hardware/software, small workforce with low training expenditure, and introducing a new innovation], increasing the workforce, then stop innovating. This involves removing innovation and adding more workforce. For labor productivity, we see the same transition as for profit, from 18 (10010) to 20 (10100). This is involves the same transitions as described for profit. Overall, we see for this industry that there are relatively small differences between the lowest and highest performing states in regards to the non-growth performance measures.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	1	-108.8998	31	4.5730885	1-0-2-18*
glprod	% change per employee	20	-0.008334	1	0.4623999	20-4-0-1
profit	$ per employee	18	0.1015109	20	2.7067863	18-22-20
lprod	$ per employee	18	104547.24	20	360321.3	18-22-20

Table 33. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (labor intensive tertiary manufacturing industry).
*** max state unattainable due to budget constraint**

3 Primary Product Manufacturing

Referring to primary product manufacturing in Table 34, for profit growth, we see a transition from 6 (00110) to 28 (11100). This corresponds to starting with [large workforce with low training expenditure and innovating], stop innovating, implement other technology, then implementing new hardware/software. Technology use and a large workforce are recommended for growing profit. For labor productivity growth, we see a transition from 22 (10110) to 5 (00101). This corresponds to starting with [implementing new hardware/software, large workforce with low training expenditure, and innovating], stop implementing new hardware/software, add more training, then stop innovating. For this case, the maximum performance state is 10 (01010) [implementing other technology, small workforce with low training, and innovating], which is quite different than state 5, the maximum attainable state, involving a large, well-trained workforce. State 10 cannot be reached while satisfying the budget constraint.

For profit margin we see a transition from 8 (01000) to 23 (10111). This corresponds to starting with [implementing other technology, small workforce with low training expenditure], stop implementing other technology, increase training expenditure, increase workforce, innovate, then implement new hardware/software. This involves the maximum number of transitions, one from a very simple state of operations to a very complex one, involving high levels of each variable except for other technology implementations outside of hardware/software. For labor productivity, we see a transition from 26 (11010) to 23 (10111). This corresponds to starting with [implementing new hardware/software and other technology, small and untrained workforce, and innovating], stop implementing other technology, increase workforce, then increase training. This transition to state 26 (same as for profit) is a slightly less complex transition.

Overall, we again see identical maximum states of performance overlapping with profit and labor productivity, as in labor intensive tertiary manufacturing. This appears reasonable since they are both in the broader sense ‘manufacturing industries’. Also note that hardware/software implementation appears to be common amongst the majority of the maximum states.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	6	-13.83427	28	84.783068	6-4-12-28
glprod	% change per employee	22	-0.028491	10	0.8754341	22-6-7-5*
profit	$ per employee	8	0.1336037	23	1.7752156	8-0-1-5-7-23
lprod	$ per employee	26	108447.47	23	526109.38	26-18-22-23

Table 34. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (primary product manufacturing industry).
* **max state unattainable due to budget constraint**

4 Secondary Product Manufacturing

In secondary product manufacturing (Table 35), for profit growth, we see a transition from 22 (10110) to 18 (10010). This corresponds to starting with [implementing new hardware/software, large workforce with low training expenditure, and innovating], then downsizing the workforce. Although state 10 [implementing other technology, innovating, and a small workforce with low level of training] is the maximum state, the highest attainable state is 18, which involves downsizing the workforce, while maintaining new hardware/software implementation(s) and innovation. State 10 cannot be reached while satisfying the budget constraint. For labor productivity growth, we see a transition from state 5 (00101) to state 31 (11111). This corresponds to starting with [large workforce with high training expenditure], adding innovation, implementing new hardware/software, then adding other technology. This means keeping all of the variables at a high level, resulting in a large and well-trained workforce, as well as technology use coupled with innovation.

For profit margin we see a transition from 28 (11100) to 18 (10010). This corresponds to starting with [implementing new hardware/software and other technology, and a large workforce with low training expenditure], stop implementing other technology, innovate, then reduce the workforce. Again, the max state (14 [implementing other technology, large workforce with a low level of training, and innovating]) is not attainable (as a result of the budget constraint), and results in using hardware/software implementation and innovations. For labor productivity, we see a transition from 10 (01010) to 3 (00011). This corresponds to starting with [implementing other technology, small workforce with low training expenditure, and innovating], stop implementing other technology, and increase training. This emphasizes a well-trained workforce with introducing process/product innovation(s).

Overall, we see a mixed-bag of results when analyzing the states from each performance variable. However, the highest attainable state for both profit variables are the same, which is due to the budget constraint.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	22	-1.109	10	38.915	22-18*
glprod	% change per employee	5	-0.0513	31	1.0932	5-7-23-31
profit	$ per employee	28	0.0319	14	0.7248	28-20-22-18*
lprod	$ per employee	10	116482	3	389661	10-2-3

Table 35. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (secondary product manufacturing industry).
* **max state unattainable due to budget constraint**

5 Capital Intensive Tertiary Manufacturing

For profit growth in the capital intensive tertiary manufacturing industry (Table 36), we see a transition from 8 (01000) to 21 (10101). This corresponds to starting with [implementing other technology and a small workforce with low training expenditure], not implementing other technology, adding new hardware software, increasing the workforce, then increasing training. This emphasizes new hardware/software implementations as well as a larger, well-trained workforce. For labor productivity growth, we see a transition from 8 (01000) to 15 (01111). This corresponds to starting with [implementing other technology and a small workforce with low training expenditure], halting implementation of other technology, innovating, increasing training expenditure, adding more workforce, then implementing other technology. Here, all variables are implemented at high levels except for new hardware/software implementation.

For profit we see a transition from 28 (11100) to 18 (10010). This emphasizes computer/hardware implementation and introducing new innovations. This corresponds to starting with [implementing new hardware/software and other technology, as well as having a large workforce with low training expenditure], halting implementation of other technology, downsizing the workforce, and then innovating. For labor productivity, we see a transition from 16 (10000) to 1 (00001). This corresponds to starting with [implementing new hardware/software and a small workforce with low training expenditure], halting implementation of new hardware/software, and then increasing training. This only emphasizes a trained workforce.

Again, we have a mixed bag of results. We can see that implementing other technologies alone seems to result in poor performance, especially if growth is the performance objective.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	8	-5.172527	21	4.9698705	8-0-16-20-21
glprod	% change per employee	8	-0.035345	15	0.5220348	8-0-2-3-7-15
profit	$ per employee	28	0.0982746	18	1.9441698	28-20-16-18
lprod	$ per employee	16	108136.51	1	308650.25	16-0-1

Table 36. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (capital intensive tertiary manufacturing industry).

6 Construction

In the construction industry (Table 37), for profit growth, we see a transition from 5 (00101) to 15 (01111). This corresponds to starting with [having a large workforce with a large training expenditure], innovating, then implementing other technology. This suggests that all variables involving workforce and technology/innovation are important, except for new hardware/software implementation. For labor productivity growth, we see a transition from 8 (01000) to 15 (01111). This corresponds to starting with [implementing other technology and a small workforce with low training expenditure], halting implementation of other technology, innovating, adding more training, adding more workforce, then implementing other technology. This result is relatively similar to the profit growth objective since the maximum state (31) [implementing new hardware/software and other technology, a large workforce with a small amount of training, and innovating] is not attainable. Since not implementing hardware/software technology reduces the budget, it is eliminated to make a feasible path in this case.

For profit margin we see a transition from 1 (00001) to 15 (01111). This corresponds to starting with [a small workforce with high training expenditure], increasing the workforce, innovating, then implementing other technology. Again, state 15 is the maximum state, as is the profit growth variable. For labor productivity, we see a transition from 8 (01000) to 15 (01111). This corresponds to starting with [implementing other technology and a small workforce with low training expenditure], halting implementation of other technology, innovating, adding more training, adding more workforce, then implementing other technology. This transition is identical to the labor productivity growth objective.

For this industry, there is a large correlation between the performance measures. Particularly, the profit variables are very similar to each other in their results as are the labor productivity variables. It appears to make sense that new computer software/hardware implementation may not be very important since construction is a more ‘hands-on’ profession and advances in this area are not as frequent.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	5	-13.774	15	40.061	5-7-15
glprod	% change per employee	8	-0.0964	31	1.9779	8-0-2-3-7-15*
profit	$ per employee	1	0.065	15	0.8898	1-5-7-15
lprod	$ per employee	8	88470	31	667566	8-0-2-3-7-15*

Table 37. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (construction industry).
*** max state unattainable due to budget constraint**

7 Transportation, Warehousing, Wholesale

In the transportation, warehousing, and wholesale industry (Table 38), for profit growth, we see a transition from 15 (01111) to 31 (11111). This corresponds to starting with [implementing other technology, having a large workforce with high training expenditure, ad innovating], then adding new software hardware. This suggests that there is a very fine line between an optimal state of operations and a minimal state, which is defined by hardware/software implementation. For optimal operations, new hardware/software is should be implemented. For labor productivity growth, we see a transition from 30 (11110) to 6 (00110). This corresponds to starting with [implementing new hardware/software and other technology, innovating, and having a large workforce with low training expenditure], halting implementation of other technology, then halting implementation of new hardware/software. This suggests that new technology is not so important compared to workforce size and innovation.

For profit we see a transition from 12 (01100) to 31 (11111). This corresponds to starting with [implementing other technology and a large workforce with low training expenditure], adding innovation, adding new hardware/software, then adding more training. Again, this result is similar to the profit growth result except that the differences between the minimal and maximal states of operations are larger. Here we see that in addition to adding new hardware/software, new innovation and an increased training expenditure should be implemented for optimal operations. For labor productivity, we see a transition from 12 (01100) to 3 (00011). This corresponds to starting with [implementing other technology and a large workforce with low training expenditure], adding innovation, adding more training, halting implementation of other technology, then reducing the workforce. This suggests moving away from technology and workforce size and moving towards more employee training as well as innovation.

Again, we see some correlation, this time with the profit performance objectives. However, we also see that labor productivity objectives correlate more with simpler states of technology.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	15	-3.4028	31	492.22	15-31
glprod	% change per employee	30	-0.1832	6	0.4093	30-22-6
profit	$ per employee	12	-0.0109	31	6.0864	12-14-30-31
lprod	$ per employee	12	113221	3	815137	12-14-15-7-3

Table 38. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (transportation, warehousing, wholesale industry).

8 Communication and Other Utilities

In the communication and other utilities industry (Table 39), for profit growth, we see a transition from 1 (00001) to 6 (00110). This corresponds to starting with [having a small workforce with high training expenditure], reducing training, innovating, then adding more workforce. This suggests less training and a larger workforce focusing on innovation. For labor productivity growth, we see a transition from 30 (11110) to 1 (00001). This corresponds to starting with [implementing new hardware/software and other technology, having a large workforce with low training expenditure, and innovating], halting innovation, reducing the workforce, halting implementing other technology, halting implementing new hardware/software, then increasing training. This suggests moving away from a more complex state of operations to a simpler, smaller and well-trained workforce.

For profit we see a transition from 17 (10001) to 23 (10111). This corresponds to starting with [implementing new hardware/software and having a small workforce with a high training expenditure], halting implementation of new hardware/software, innovating, adding more workforce, then adding new hardware/software. This suggests increasing innovation and hiring more employees. For labor productivity, we see a transition from 10 (01010) to 23 (10111). This corresponds to starting with [implementing other technology, innovating and having a small workforce with low training expenditure], halting implementation of other technology, adding more training, adding more workforce, then adding new hardware/software. This implies focusing on growing to a large, well-trained workforce as well as more innovation and implementation of new hardware/software.

It's odd that the two growth performance measures include the same state (1) [having a small workforce with high training expenditure] being optimal for one measure (glprod) and minimal for the other (gprofit). This shows that labor productivity and profit don't always correlate, thus this phenomena can occur. However, the non-growth measures have the same maximal states.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	1	-5.6381	6	55.294	1-0-2-6
glprod	% change per employee	30	-0.1265	1	0.8666	30-28-24-16-0-1
profit	$ per employee	17	0.0046	23	0.5801	17-1-3-7-23
lprod	$ per employee	10	102033	23	578366	10-2-3-7-23

Table 39. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (communication and other utilities industry).

9 Retail Trade and Consumer Services

Optimal profit growth in the retail trade and consumer services industry (Table 40) is characterized by a transition from 18 (10010) to 22 (10110). This corresponds to starting with [implementing new hardware/ software, innovating, and having a small workforce with low training expenditure], halting implementation of new hardware/software, adding more workforce, then adding new hardware/software. This suggests that the only difference between a failing company and a thriving one is the size of the workforce (size). Specifically, size is of great importance. This result appears to suggest that larger business (e.g. Walmart) dominate similar yet smaller businesses (e.g. 'mom-and-pop' stores). For labor productivity growth, we see a transition from 12 (01100) to 0 (00000). This corresponds to starting with [implementing other technology and having a large workforce with low training expenditure], halting implementation of other technology, then reducing the workforce. This suggests that keeping operations at a minimum is the best option under the given constraints. Notice that the optimal state (18) [implementing new hardware/ software, innovating, and having a small workforce with low training expenditure] is not attainable, so minimalism is not necessarily the best option overall.

For profit margin we see a transition from 12 (01100) to 14 (01110). This corresponds to starting with [implementing other technology and having a large workforce with low training expenditure], halting implementing other technology, innovating, then implementing other technology. This suggests that product/process innovation is critical to success in the industry. For labor productivity, we see a transition from 12 (01100) to 21 (01111). This corresponds to starting with [implementing other technology and having a large workforce with low training expenditure], halting implementing other technology, adding more training, then adding new hardware/software. Again, product/process innovation appears to be important along with a trained workforce. Also, state 15 (maximum state) is not attainable due to the budget constraint.

Overall, there appears to be a correlation with innovation and success. Also, investing in other technologies and having a larger workforce alone does not seem to be a productive combination in this industry. The costs associated with reaching some of the states are infeasible, thus resulting in less than the theoretically optimal final state of operation.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	18	-23.131	22	12.975	18-2-6-22
glprod	% change per employee	12	-0.2669	18	0.5457	12-4-0*
profit	$ per employee	12	0.1846	14	1.5505	12-4-6-14
lprod	$ per employee	12	68648	15	291554	12-4-5-21*

Table 40. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (retail trade and consumer services industry).
* **max state unattainable due to budget constraint**

10 Finance and Insurance

For the finance and insurance industry (Table 41), profit growth has a transition from 4 (00100) to 30 (11110). This corresponds to starting with [having a large workforce with low training expenditure], innovating, adding other technology, then adding new hardware/software. This suggests that a large workforce needs to be supported by technology and innovation. Notice that state 18 [implementing new hardware/ software, innovating, and having a small workforce with low training expenditure] is the overall maximum state and is not attainable due to the budget constraint. For labor productivity growth, we see a transition from 14 (01110) to 15 (01111). This corresponds to starting with [implementing other technology, having a large workforce with low training expenditure, and innovating], then increasing training expenditure. This suggests that training is critical with technology and innovation. This makes sense since often times employees need training to use technology and create new products and processes.

For profit we see a transition from 1 (00001) to 31 (11111). This corresponds to starting with [having a small workforce with high training expenditure], innovating, adding to the workforce, reducing training, adding other technology, then adding more training, then adding new hardware/software. This suggests that training alone is not useful, and in fact if costs are no factor, removing training altogether is best while keeping all the other variables of interest (i.e. software/hardware, innovation, and workforce size) high. For labor productivity, we see a transition from 18 (10010) to 31 (11111). This corresponds to starting with [implementing new hardware/software, innovating, and having a small workforce with low training expenditure], adding to the workforce, adding more training, then implementing other technology. Again, the maximal state, state 17 [implementing new hardware/software ad having a small workforce with high training expenditure], is unattainable, which leads to a more complex solution involving all of the variables of interest (i.e. software/hardware, innovation, workforce size, and training expenditure) at high levels of operation.

A firm in the finance and insurance industry appears to spend high amounts on technology (i.e. higher than industry average) when working optimally. This leads to less than optimal states of operation when trying to keep technology costs at or below the industry average, which is assumed by the budget constraint.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	4	-1.518344	18	247.29392	4-6-14-30*
glprod	% change per employee	14	-0.055135	15	12.018758	14-15
profit	$ per employee	1	0.2721279	30	1.4859543	1-3-7-6-14-15-31*
lprod	$ per employee	18	129455.25	17	330694.85	18-22-23-31*

Table 41. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (finance and insurance industry).
* **max state unattainable due to budget constraint**

11 Real Estate, Rental and Leasing Operations

Profit growth in the real estate, rental and leasing operations industry (Table 42) is characterized by a transition from 1 (00001) to 20 (10100). This corresponds to starting with [having a small workforce with high training expenditure], reducing training, adding more workforce, then adding new hardware/software. This suggests that training is not as important as a large workforce and new hardware/software implementations. For labor productivity growth, we see a transition from 31 (11111) to 0 (00000). This corresponds to starting with [implementing new hardware/software and other technology, innovating, and having a large workforce with high training expenditure], halting implementation of other technology, halting innovating, halting implementation of new hardware/software, then, reducing training, then reducing the workforce. This is due to the fact that state 22 is not attainable, thus simple operating conditions (i.e. no new hardware/software or other technologies, no innovations, small workforce and little training) are reasonable.

For profit we see a transition from 20 (10100) to 6 (00110). This corresponds to starting with [implementing new hardware/software and having a large workforce with small training expenditure], halting implementing new hardware/software, then adding innovation. This suggests that a large workforce works better with innovation compared to a large workforce with hardware/software innovation. For labor productivity, we see a transition from 4 (00100) to 7 (00111). This corresponds to starting with [having a large workforce with low training expenditure], adding more training, then creating innovation. This suggests adding innovation and more training to a large workforce.

There appears to be mixed results with this industry. It's interesting that state 20 is both a maximum state for profit growth and a minimal state for profit margin. So although implementing new software/hardware and having a large workforce can help grow the firm, it can also be seen as a detrimental state of operation if short-term success is desired. This makes sense since a large workforce backed with new technology is generally a breeding ground for growth, whereas cutting workforce size and spending less of the budget on technology can cut costs, resulting in short term success.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	1	-5.80781	20	38.923805	1-0-4-20
glprod	% change per employee	31	-0.13772	22	0.4759314	31-23-21-5-4-0*
profit	$ per employee	20	0.0586435	6	0.6985946	20-4-6
lprod	$ per employee	4	144961.82	7	336318.8	4-5-7

Table 42. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (real estate, rental and leasing operations industry).
* **max state unattainable due to budget constraint**

12 Business Services

Profit growth in the business services industry (Table 43) is characterized by a transition from 22 (10110) to 18 (10010). This corresponds to starting with [implementing new hardware/software, innovating, and having a large workforce with low training expenditure], then reducing the size of the workforce. This suggests that hardware/software and innovation are important, but not when coupled with a large workforce. For labor productivity growth, we see a transition from 22 (10110) to 19 (10011). This corresponds to starting with [implementing new hardware/software, innovating, and having a large workforce with low training expenditure], halting implementation of new hardware/software, reducing the workforce, adding more training, then adding new hardware/software. Again, this suggests that hardware/software and innovation are important, but not when coupled with a large workforce (size). In addition training is stressed as well.

For profit we see a transition from 23 (10111) to 20 (10100). This corresponds to starting with [implementing new hardware/software, innovating, and having a large workforce with high training expenditure], halting innovation, then reducing training. This suggests a large workforce combined with new hardware/software implementation is important. For labor productivity, we see a transition from 4 (00100) to 20 (10100). This corresponds to starting with [having a large workforce with low training expenditure], adding more training, adding new hardware/software, then reducing training. This is similar to the profit results, except that the weakest state is when a large workforce is completely unsupported.

Overall, we see that the weakest state of operations usually involves a combination of a large workforce, innovation, and hardware/software implementation. The optimal state tends to use a combination of hardware/software with either a large workforce or innovation, but not both. This suggests that workforce and innovation are substitutes for the business services industry. Again, there seems to be a “fine line” between optimal and weak states of operation. That is, there is often just one operational change needed to take a firm from the minimum performance state to the maximum performance state.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	22	-2.658246	18	15.685049	22-18
glprod	% change per employee	22	-0.174406	19	1.4921825	22-6-2-3-19
profit	$ per employee	23	0.1341839	20	2.9314349	32-21-20
lprod	$ per employee	4	131684.84	20	339017.05	4-5-21-20

Table 43. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (business services industry).

13 Education and Health Services

Profit growth in the educational and health service industry (Table 44) is characterized by a transition from 19 (10011) to 4 (00100). This corresponds to starting with [implementing new hardware/software, innovating, and having a small workforce with high training expenditure], halting implementing new hardware/software, reducing training, halting innovation, then adding more workforce. This involves simplifying operations by removing new hardware/software implementations, innovation, and training, as well as increasing the workforce. For labor productivity growth, we see a transition from 7 (00111) to 2 (00010). This corresponds to starting with [innovating and having a large workforce with high training expenditure], reducing the workforce, then reducing training. This suggests simplifying again; this time by reducing the workforce and their associated training, but continue to innovate. This may seem counterproductive since training often times is associated with increased innovation. Note that the maximum state (18) [implementing new hardware/software, innovating, and having a small workforce with low training expenditure] is not feasible in this case.

For profit we see a transition from 7 (00111) to 0 (00000). This corresponds to starting with [innovating and having a large workforce with high training expenditure], reducing the workforce, reducing training, then halting innovation. Again, simplification is occurring, due to an unattainable optimal state (18 [implementing new hardware/software, innovating, and having a small workforce with low training expenditure]). As a result, the simplest state of operations is implemented since it is the maximum performance state that is attainable in regards to budget. For labor productivity, we see a transition from 4 (00100) to 0 (00000). This corresponds to starting with [having a large workforce with low training expenditure], then reducing the workforce. Again, simplification of the solution occurs due to an unattainable state (state 17 [implementing new hardware/software, and having a small workforce with high training expenditure]).

In this case, the best states generally involve new hardware/software innovation coupled with either a high level of training or innovation, but are reduced to simpler states due to unattainable optimal states.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	19	-43.26308	4	11.052737	19-3-2-0-4
glprod	% change per employee	7	-0.063764	18	0.4455318	7-3-2*
Profit	$ per employee	7	0.111232	18	0.9480429	7-3-2-0*
Lprod	$ per employee	4	64459.73	17	124189.43	4-0*

Table 44. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (education and health services industry).
* **max state unattainable due to budget constraint**

14 Information and Culture

In the information and cultural industry (Table 45), profit growth transitions from 18 (10010) to 4 (00100). This corresponds to starting with [implementing new hardware/software, innovating, and having a small workforce with low training expenditure], halting implementation of new hardware/software, adding to the workforce, then halting innovation. This suggests a large workforce takes priority over technology and innovation. For labor productivity growth, we see a transition from 22 (10110) to 21 (10101). This corresponds to starting with [implementing new hardware/software, innovating, and having a large workforce with low training expenditure], halting innovation, then adding more training. This suggests that technology is better grouped with a large trained workforce instead of a large workforce that innovates.

For profit we see a transition from 22 (10110) to 3 (00011). This corresponds to starting with [implementing new hardware/software, innovating, and having a large workforce with low training expenditure], halting the implementation of new hardware/software, adding more training, then reducing the workforce. This suggests that a small, well-trained workforce that innovates is superior to a large innovative workforce that implements new hardware/software. For labor productivity, we see a transition from 4 (00100) to 31 (11111). This corresponds to starting with [having a large workforce with low training expenditure], innovating, adding more training, implementing other technology, then implementing new hardware/software. This suggests that a large workforce alone is inferior to a large, technology-drive, innovative, and trained workforce.

Once again, there is a mixed-bag of contradictive results. State 4 is both a maximum state and a minimum state for two separate performance measures (gprofit and Lprod). There appears to be no clear-cut strategy that encompasses them all. In cases such as this, managers would be best to pick the most important performance measure to obtain their strategy. Often times profit growth is considered most important, but because so many variables affect it, sometimes labor productivity growth is used for clearer justification.

	Units of Measure	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	% change per employee	18	-6.202745	4	8.6593206	18-2-6-4
Glprod	% change per employee	22	-0.070392	21	0.4667498	22-20-21
Profit	$ per employee	22	0.1185101	3	1.7132772	22-6-7-3
Lprod	$ per employee	4	109722.26	31	248816.04	4-6-7-15-31

Table 45. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (information and cultural industries).

Conclusions

When the maximum state is not attainable due to the budget constraint, often times the optimal path involves an end state that consists of lower technology implementation. This is expected to occur since the budget constraint is limited by technology costs. The associated variables pertaining to technology implementation (Tech1 and Tech23, referring to hardware/software and other technologies) are often the ones that are eliminated early on in the optimal paths as well, since they reduce the overall yearly costs involved with the budget constraint. The two non-growth performance measures appeared to have given similar results in many cases in terms of maximum states.

Although there is often some correlation between optimal state and performance measures within an industry, there are a few industries that have contradictive strategies. These industries include the communication and other utilities industry, the real estate, rental and leasing operations industry, and the information and culture industry. For example, there are cases shown where the same state is a maximal state under one performance measure and a minimal state under another. This leads to unclear overall strategies for the industry. This phenomena can occur due to the variables that make up each of the performance measures. For example, profit may be greatest when there is a large workforce, but that same large workforce could decrease labor productivity.

An overall summary of the maximum attainable state organizational attributes for each industry/performance measure is listed in Table 46. We can see that having new hardware and software upgrades are important for the following industries:

- Labor Intensive Tertiary Manufacturing
- Primary Product Manufacturing
- Secondary Product Manufacturing
- Finance and Insurance
- Business Services

Implementing other new technology appears to be correlated well with these industries:

- Construction
- Finance and Insurance

Obtaining a large workforce appears to be beneficial for the following industries:

- Primary Product Manufacturing
- Capital Intensive Tertiary Manufacturing
- Construction
- Transportation, Warehousing, Wholesale
- Communication and Other Utilities
- Retail Trade and Consumer Services

- Finance and Insurance
- Real Estate, Rental and Leasing Operations
- Information and Culture

Innovation appears to work well in the following industries:

- Secondary Product Manufacturing
- Construction
- Transportation, Warehousing, Wholesale
- Communication and Other Utilities
- Finance and Insurance

And finally, Training appears significant in the following industries:

- Forestry, Mining, Oil and Gas Extraction
- Primary Product Manufacturing
- Capital Intensive Tertiary Manufacturing
- Construction
- Transportation, Warehousing, Wholesale
- Communication and Other Utilities
- Finance and Insurance
- Information and Culture

Industry	% of unattainable maximum state CSP solutions	New Hardware or Software?	Other New Technology?	Large Workforce?	New Product or Process Innovation?	Large Training Expenditure Per Employee?
Forestry, Mining, Oil and Gas Extraction	50			profit		lprod, glprod, profit
Labor Intensive Tertiary Manufacturing	25	lprod, profit, gprofit		lprod, profit	grpofit	glprod
Primary Product Manufacturing	25	lprod, profit, gprofit	grofit	lprod, profit, gprofit, glprod	lprod, profit	lprod, profit, glprod
Secondary Product Manufacturing	50	profit, gprofit, glprod	glprod		profit, gprofit, lprod	lprod
Capital Intensive Tertiary Manufacturing	0	profit, gprofit		glprod, gprofit, lprod	glprod, profit	glprod, gprofit, lprod
Construction	50		All vars	All vars	All vars	All vars
Transportation, Warehousing, Wholesale	0	profit, gprofit	profit, gprofit	All vars	All vars	All vars
Communication and Other Utilities	0	lprod, profit,		All vars	All vars	All vars
Retail Trade and Consumer Services	50	gprofit, lprod	profit	gprofit, profit, lprod	gprofit, profit	lprod
Finance and Insurance	75	gprofit, profit, lprod	All vars	All vars	All vars	glprod, profit, lprod
Real Estate, Rental and Leasing Operations	25	gprofit		gprofit, profit, lprod	profit, lprod	lprod
Business Services	0	All vars		profit, lprod	gprofit, glprod	glprod
Education and Health Services	75			gprofit	glprod	
Information and Culture	0	glprod, lprod	lprod	gprofit, glprod, lprod	profit, glprod	glprod, profit, lprod

Table 46. Summary of the attributes possessed for each performance variable in each industry by the maximum attainable states examined in the WES dataset using CSP methods (also included is the number of unattainable maximum states by industry)

Also, an overall summary of the optimal shortest path step-by-step changes to the organizational structure for each industry/performance measure, as it pertains to traversing from the industry average minimum state of operations to the maximum (attainable) state of operations in shown in Table 47.

We can see that for the forest, mining, oil and gas extraction industry, computers and innovation are not considered to important and are thus removed in early stages of the algorithm.

For labor intensive tertiary manufacturing, static measures of performance appear to be correlated with increasing the workforce and removing innovation. Primary product manufacturing static measures appear to be correlated with removing other forms of technology first, then adding a larger, highly trained workforce. Secondary product manufacturing is also associated with removing new forms of other technologies and adding training and innovation, in terms of static measures. Finally, for capital intensive tertiary manufacturing, removing new other technologies early on and then adding in training and workforce, and often time innovation is suggested by the algorithms. For manufacturing as a whole, it appears that implementing new technologies is not of much importance and adding a well-trained workforce and possibly innovation as well is a trend for high levels of success.

For construction, adding innovation early on, then training, workforce, and other technologies is the preferred path for success. Implementing computer technology and then training the workforce is suggested for the transportation, warehousing, and wholesale industry. Removing other technologies early on and then increasing the workforce, and then adding computer technology is a suggested trend in the communication industry. For the retail trade and consumer services industry, removing the additions of other technology and adding technology later is the suggested route of organizational changes. Adding innovation early on, and then training and some form of technology later on is the recommended path for the finance and insurance industry. Adding innovation appears to be a recommended strategy for the real estate, rental and leasing operations in terms of static performance measures. Adding computer technology at some point is recommended for the business services industry. Reducing the workforce, training, and then innovation is recommended for the education and health services industry. And finally, adding more training relatively early on seems to be recommended in the information and culture industry.

Overall, there appears to be a trend in removing practices (and particularly technology) early on as well as adding practices (especially technology) towards the end of the recommended paths. This is most likely due to reducing the expenses early on and adding them in later, so as to stay under the budgets created in the CSP models. It is logical that if a firm wants to make changes and stay under its budget, removing practices (particularly technology and innovation) early on is a good idea in general. Also, in regards to evolutionary economics theory, adding in new technology after adjusting supporting aspects of the firm, such as training and workforce levels, is a recommended policy and is confirmed here. However, evolutionary economics theory would also suggest that innovation be added in with support of other organizational practices. This does not hold in our CSPP results, where we can see that innovation is often times added to the operational state early on the sequences.

Industry	Performance Measure Examined	Change 1	Change 2	Change 3	Change 4	Change 5	Change 6
Forestry, Mining, Oil and Gas Extraction	**Gp**	- computer	- innov.	- training			
	Gl	- computer	- innov.	- workforce	+ training		
	P	- computer	- innov.	+ computer			
	L	- computer	- other tech	- innov.	- workforce	+ training	
Labor Intensive Tertiary Manufacturing	**Gp**	- training	+ innov.	+ computer			
	Gl	- computer	- workforce	+ training			
	P	+workforce	- innov.				
	L	+workforce	- innov.				
Primary Product Manufacturing	**Gp**	- innov.	+other tech	+ computer			
	Gl	- computer	+ training	- innov.			
	P	- other tech	+ training	+workforce	+ innov.	+ computer	
	L	- other tech	+workforce	+ training			
Secondary Product Manufacturing	**Gp**	- workforce					
	Gl	+ innov.	+ computer	+other tech			
	P	- other tech	+ innov.	- workforce			
	L	- other tech	+ training				
Capital Intensive Tertiary Manufacturing	**Gp**	- other tech	+ computer	+workforce	+ training		
	Gl	- other tech	+ innov.	+ training	+workforce	+other tech	
	P	- other tech	- workforce	+ innov.			
	L	- computer	+ training				
Construction	**Gp**	+ innov.	+other tech				
	Gl	- other tech	+ innov.	+ training	+workforce	+other tech	
	P	+workforce	+ innov.	+other tech			
	L	- other tech	+ innov.	+ training	+workforce	+other tech	
Transportation, Warehousing, Wholesale	**Gp**	+ computer					
	Gl	- other tech	- computer				
	P	+ computer	+ training				
	L	+ innov.	+ training	- other tech	- workforce		
Communication and Other Utilities	**Gp**	- training	+workforce				
	Gl	- innov.	- workforce	- other tech	- computer	+ training	
	P	- computer	+ innov.	+workforce	+ computer		
	L	- other tech	+ training	+workforce	+ computer		
Retail Trade and Consumer Services	**Gp**	- computer	+workforce	+ computer			
	Gl	- other tech	- workforce				
	P	- other tech	+ innov.	+other tech			
	L	- other tech	+ training	+ computer			
Finance and Insurance	**Gp**	+ innov.	+other tech	+ computer			
	Gl	+ training					
	P	+ innov.	+workforce	- training	+other tech	+ training	+computer
	L	+workforce	+ training	+other tech			

Table 47. Step-By-Step (In Order) Organizational Changes Recommended By CSP Method From Minimum State of Operations to Maximum Attainable State (From Section 5.2.2 Results)

Note: Gp – profit growth; Gl – labor productivity growth; P – profit; L – labor productivity;
'-' ('+') represents removing (adding) the organizational practice;

*** Table 47 continues on next page**

Industry	Performance Measure Examined	Change 1	Change 2	Change 3	Change 4	Change 5	Change 6
Real Estate, Rental, and Leasing Operations	**Gp**	- training	+workforce	+ computer			
	Gl	- other tech	- innov.	- computer	- training	-workforce	
	P	- computer	+ innov.				
	L	+ training	+ innov.				
Business Services	**Gp**	-workforce					
	Gl	- computer	-workforce	+ training	+ computer		
	P	- innov.	- training				
	L	+ training	+ computer	- training			
Education and Health Services	**Gp**	- computer	- training	- innov.	+workforce		
	Gl	-workforce	- training				
	P	-workforce	- training	- innov.			
	L	-workforce					
Information and Culture	**Gp**	- computer	+workforce	- innov.			
	Gl	- innov.	+ training				
	P	- computer	+ training	-workforce			
	L	+ innov.	+ training	+other tech	+ computer		

Table 47. (Continued from previous page) Step-By-Step (In Order) Organizational Changes Recommended By CSP Method From Minimum State of Operations to Maximum Attainable State (From Section 5.2.2 Results)

Note: Gp – profit growth; Gl – labor productivity growth; P – profit; L – labor productivity;
'-' ('+') represents removing (adding) the organizational practice;

6 Conclusions & Discussion

The algorithms used in the research appear to have not previously been used in regards to organizational management and thus many of the findings generated are the first of this nature and can only be compared to results found using other empirical methods of research. Hence, the results further expand on previous literature.

Much previous research in regards to innovation, technology, human resource practices, training, and other supporting organizational management practices has been done on a broad scale, with theoretical and empirical results leading to one or two broad conclusions. Those conclusions usually suggest combining organizational practices, such as training, with technology and innovation implementation. In evolutionary economics theory, it is said that innovation and technology needs to be preceded by the supporting organizational structures (HRM practices, training, etc.) and the right personnel (educated individuals working as a team) in place before innovation and technological growth can flourish. Through this research, the evidence shows that one general theory does not hold true for all industries or even within each industry itself. Rather, there appears to be multiple combinations of organizational practices adopted in different orders that result in success, depending on what one chooses to base "success" on. Path-dependencies shown in the results are not always in line with the general theory. This shows that there is probably potential to this method in terms of breaking some stereotypes that a certain organizational structure must exist to be successful.

Through the investigations made on the industry level, we have found that performance measures have a significant effect on what organizational strategies to implement. Generally, the best practices using profit as the measure of performance are not the same as using labor productivity as the performance measure. This also generally holds true when comparing results using a static performance variable and its associated growth measure.

The CSPP algorithm developed for this dissertation has the potential to add significant insights for managers in the sense that the algorithm can take in any number of factors of interest, including any constraints on (or a combination of) said factors. Then the method can give optimal (and/or near optimal) solutions to the manager. In addition, it creates a list of step-by-step changes to follow to satisfy constraints, such as budgets, through the change process. The step-by-step method also serves an advantage in that it allows managers the option to plan gradual organizational changes so as to potentially minimize complications in the process.

Another application of the information gathered in this thesis is for a firm to use a “best practice benchmarking” procedure. This would involve the organization to evaluate various aspects of their organization in relation to the “best practice” found within their own industry (e.g. the combinations of operations yielding the highest performance values, as indicated by the industry averages extracted from the dataset). The firm could then develop its own plan on how to make improvements or use the suggestions from the CSPP algorithm.

The proposed CSPP algorithm clearly outperforms the CRW and D&B algorithms in the randomized tests used on single and multiply-constrained (up to 20) shortest path problems. Fairly large datasets ranging from 23 variables of interest (256 vertices and 704 edges) to 23 variables (8,388,608 vertices and 21,344 edges) were randomly generated and each ran on the three algorithms. The results are positive in the sense that the amount of time saved by use of the CSPP algorithm appears to be of a constant magnitude faster than the other two methods. This is a reasonable result, as the CSPP algorithm is based off the CRW algorithm with modifications to save processing steps under certain situations, mainly through the use of additional aggregated bounds on the side constraints and re-optimizing the Lagrangian lower bound periodically. Otherwise, CSPP acts in a similar way as the CRW algorithm. All of the algorithms have exponential worst-case complexity and computation time.

There are several areas of future directions this research could explore. Further research within the given dataset could be applied to individual employees' success, by using the variables associated with the employees while using a performance measure such as compensation. Most of this research used a dataset with a relatively limited number of variables in some areas of organizational management, such as technology. The methods described could additionally be applied to other datasets in the areas of technology management or general organizational management. This could delve into specific areas of management, such as human resource management, where there are many more possible variables to explore. The results can be compared to past empirical studies on the same datasets to aid in further understanding.

The algorithms, including the proposed method, could potentially be explored and refined for increased speed and greater efficiency in order to handle larger, more complex datasets. Some possible enhancements include adding aggregated constraints to remove the possibility of traversing infeasible paths and decomposing the problem into multiple subproblems where every feasible path must include the same specific edge (Carlyle, Royset and Wood, 2006).

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Appendix

Appendix A. Code for Lagrangian Relaxation Enumeration Method

A.1 Main Function for Lagrangian Relaxation Method

```
function [xstar] =
LREsubroutine(adjmatrix,s,t,c,F,g,lambda,xhat,zlambda,delta)
%%%%%%%%%%%%%%%%% Inputs %%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% adjmatrix = edge-incidence matrix for the graph
% s = start node
% t= end node
% c = edge cost vector
% F, g = side constraint data for the edges
% lambda = Lagrangian vector for CSPLR
% xhat = starting solution
% zlambda = lower bound
% delta = parameter used for criterion for near-optimal solutions


%%%%%%%%%% Outputs %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% xstar = optimal solution

% convert edge-incidence matrix to adjacency list format
adjlist = adjmatrix2list(adjmatrix);

 c =ones(1,length(F));

 b=zeros(n,1);
 for i=1:n
     if i==s
         b(i)=1;
     end
     if i==t
         b(i)=-1;
     end
 end

xstar = xhat;
 zbar = c*xstar;
cprime = c+lambda*F;
Iplus=size(F,1)+1;
fzero=c;
gzero=zbar;

Fprime = [fzero;F];
gprime = [gzero;g];


cprimeMatrix=inf(size(adjmatrix));
index=0;
```

```
for i=1:length(adjlist)
    cprimeMatrix(i,i)=0;
    for j=1:length(adjlist{i})
        cprimeMatrix(i,adjlist{i}(j))=cprime(index+j);
    end
    index=index+length(adjlist{i});
end

for i=1:n
 [SP,SPCost] = ShortestPath(cprimeMatrix, i, t);
 dprime(i) = SPCost;
end

for k=1:Iplus

    FprimeMatrix = inf(size(adjmatrix));
    index=0;
    for i=1:length(adjlist)
        FprimeMatrix(i,i)=0;
        for j=1:length(adjlist{i})
            FprimeMatrix(i,adjlist{i}(j))=Fprime(k,index+j);
        end
        index=index+length(adjlist{i});
    end

    for l=1:n
        [SP,SPCost] =ShortestPath(FprimeMatrix, l, t);
        dprimef(k,l)= SPCost;
    end
end


% initialise the first edge pointers for each vertex
nextEdgeIndex = ones(1,n);

% Initialise path length with the lagrangian constant term
L(s)= -lambda*g;
for i=1:Iplus
    % intital path weight with respect to f_i = 0
    Lf(i,s) = 0;
end

theStack = s;  onStack(s)= true; u=s;
for i=1:n
    if i~=s
        onStack(i)=false;
    end
end

while length(theStack)~=0
    1

    % update u -> the element on top of the stack
    u=theStack(length(theStack));
```

```
    if nextEdgeIndex(u) <= length(adjlist{u})-1

        nextEdgeIndex(u)=nextEdgeIndex(u)+1;
        nextEdge = adjlist{u}(nextEdgeIndex(u));

        % find index for edge cost matrices
        index = 0;
        i=1;
        while i < u
            index = index + length(adjlist{i});
        end

        tester=[];
        gprimetest=[];
        for i=1:Iplus
                tester = [tester, Lf(i,u) + Fprime(i,index +
nextEdgeIndex(u))+ dprimef(i,nextEdge)];
                gprimetest= [gprimetest, gprime(i)];
        end

        if onStack(adjlist{u}(nextEdgeIndex(u)))==false ...
            && ...
            L(u)+ cprime(index + nextEdgeIndex(u)) + dprime(nextEdge) <
zbar-delta ...
            && ...
            tester <= gprime

            if nextEdge == t %improvement is found%

                xhat=zeros(length(c),1);
                fullStack=[theStack,nextEdge];
                for i=1:length[theStack,nextEdge]-1
                    %Need to properly update edge-incidence vector xhat
                    index2=0;
                    for j=1:fullStack(i)
                        if j==fullStack(i)
                           index2=index2+ nextEdgeIndex(j);
                           xhat(index2)=1;

                        else
                            index2=index2+length(adjlist{j});
                        end
                    end
                end
                    zbar=c*xhat;
                    gzero= zbar;
                    xstar=xhat;

                    %  termination possible at this point
                    if zbar-zlambda<=delta
                        return
                    end
            else
                theStack=[theStack, nextEdge];
                onStack(nextEdge)=true;
```

```
                L(nextEdge)=L(u)+c(index+nextEdgeIndex(u));
                for i=1:Iplus
                    Lf(i,nextEdge)= Lf(i,u)+ dprimef(i,nextEdge);
                end
            end
        end
    else

       % Pop u from the stack
        theStack = theStack(1:length(theStack)-1);
        onStack(u) = false;
        nextEdgeIndex(u) = 1;

    end
end
```

A.2 Shortest Path Function (for two nodes)

```
function [SP,SPCost] = ShortestPath(CostMatrix, s, t);

% Takes CostMatrix input and finds the shortest path between vertices s
% and t. The shortest path is returned in matrix SP. For example, the %
shortest path from vertex s=4 to t=7 may be from 4 to 2 to 8 to 7. Then
% SP will be SP = [4 2 8 7].

global Global_P_Mat_for_SP;
Global_P_Mat_for_SP = 0;
global GlobalSP_Index;
global GlobalSP_Matrix;
GlobalSP_Index = 0;
D = 0;
[D, Global_P_Mat_for_SP] = AllPairsShortestPath (CostMatrix);

if (D==0)
    SP = D;
    SPCost=-inf;
elseif (D(s,t)==inf)
    SP = nan;
    SPCost=D(s,t);
    disp('The two input vertices are not connected to each other, hence
shortest path does not exist');
else
    RecursiveShortestPathComputor(s,t);
    SP = GlobalSP_Matrix;
    SPCost=D(s,t);
end

clear global Global_P_Mat_for_SP;
clear global GlobalSP_Index;
clear global GlobalSP_Matrix;
```

A.3 Shortest Path Function (for all pairs of nodes in a graph)

```
function [D, P] = AllPairsShortestPath (CostMatrix);

% Compute all pairs shortest path
% matrix D. Input is cost matrix, outputs - D is cost of shortest path
% matrix and P is previous vertex of shortest path matrix.

% Note that when there is a negative-weight cycle in the given graph,
% then D=0 will be returned and an error message is displayed. The main
% program does not display the shortest path matrix in this case.

D = 0; P = 0;
n = size (CostMatrix,1); %Number of vertices
D = CostMatrix;
for i = 1:n
    for j = 1:n
        if ((i==j)||(CostMatrix(i,j)==inf))
            P(i,j)=nan;
        else
            P(i,j)=i;
        end
    end
end

for k = 1:n
    for i = 1:n
        for j = 1:n
            if ((D(i,j))<=(D(i,k)+D(k,j)))
            else
                D(i,j) = D(i,k)+D(k,j);
                P(i,j) = P(k,j);
            end
        end
    end
end

for i = 1:n
    if (D(i,i)<0)
        disp('There is a negative-weight cycle in the graph, shortest
paths cannot be computed');
        D = 0;
        break;
    end
end
```

A.4 Recursive Shortest Path Computor

```
function [] = RecursiveShortestPathComputor(s,t);

global GlobalSP_Index;
global GlobalSP_Matrix;
global Global_P_Mat_for_SP;

if (s==t)
    GlobalSP_Index = GlobalSP_Index + 1;
    GlobalSP_Matrix(GlobalSP_Index) = s;
else
    if (Global_P_Mat_for_SP(s,t)==nan)
        disp('There is no path between these two vertices');
    else
        RecursiveShortestPathComputor(s,Global_P_Mat_for_SP(s,t));
        GlobalSP_Index = GlobalSP_Index + 1;
        GlobalSP_Matrix(GlobalSP_Index) = t;
    end
end
```

A.5 Adjacency Matrix to Adjacency List Converter

```
function adj_list = adjmatrix2list(A)
n = size(A,1);

for i=1:n
    I = find( and( A(i,:)>0,  A(i,:)~=Inf) );
    adj_list{i} = I;
end
```

A.6 Subgradient Optimization Method to Find Lagrangian Lower Bound (z(λ))), the Vector λ, and a Feasible Path x (if one is found)

```
% Uses subgradient optimization to find good lower bound for lambda
function [x,z,lambda] = subgradientopt(A,F,b,g)

lambda=2;
 mu=2;
 theta=0;
epsilon=2;

 BigA=[A;lambda*F];
 BigB=[b;lambda*g];

 x=BigA\BigB;

 while abs(cx+lambda(A*x-b))>=epsilon

    % if solution found
    if (length(sol)=length(BigB))
         % Update upper bound
        UB = c*x;
        theta=mu*(UB-(cx+lambda(A*x-b)))/norm(A*x-b,2);
        lambda=lambda+theta*(A*x-b);
    end

    %Update
    BigA=[A;lambda*F];
    BigB=[b;lambda*g];
    x=BigA\BigB;

 end
```

Appendix B. State Means

State # (bin)	00000	00001	00010	00100	00101	00110	00111	01000	01100	01110
State # (dec)	0	1	2	4	5	6	7	8	12	14
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	0.2809	0.4317	-1.642	1.0976	0.9303	0.926	0.6524	0.1221	-0.2062	0.027
glprod	0.3494	**4.5624**	0.1775	0.0779	-0.0081	0.2095	0.1623	0.3118	0.136	0.3248
Totalcost	0	0	0	0	0	0	0	63722	509234	237079
profit	0.449	1.1454	0.3727	0.2458	0.6255	0.167	0.821	0.2791	0.5284	0.4393
lprod	316831	2E+06	197270	280341	825188	171663	1E+06	328014	320524	238250
TTL_EMP	4.6801	5.1551	4.2284	65.28	114.58	154.9	136.39	4.5801	100.8	131.1
ProcProd	0	0	1	0	0	1	1	0	0	1
TRNG_EXPN	266.89	7479.9	327.67	9978	186933	11914	210562	274.38	12745	18279
cost/employee	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**13913**	**5052.1**	**1808.5**

State # (bin)	01111	10000	10001	10100	10101	10110	10111	11110	11111
State # (dec)	15	16	17	20	21	22	23	30	31
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	0.8626	0.206	**3.3814**	-0.6043	0.4143	-0.7366	**-1.9375**	-0.1667	0.8601
glprod	2.2889	0.3234	0.0064	-0.0099	0.4018	**-0.1788**	0.0457	-0.1624	0.5214
Totalcost	314083	2613.4	86490	71750	192813	291797	201802	1E+06	618304
profit	0.1079	0.433	1.3559	0.058	**3.4844**	0.1682	**0.0452**	0.2022	0.3919
lprod	199360	191946	1E+06	190748	**6E+06**	202593	236016	**164093**	165246
TTL_EMP	99.943	4.4059	8.8632	73.013	145.45	76.247	159.4	164.84	165
ProcProd	1	0	0	0	0	1	1	1	1
TRNG_EXPN	126246	41.321	10180	14062	289390	13522	259025	52280	210954
cost/employee	**3142.6**	**593.16**	**9758.3**	**982.71**	**1325.6**	**3827**	**1266**	**8192.4**	**3747.3**

Table 48. State Means (Industry 01: forestry, mining, oil, and gas extraction)

Variable	Mean
Totalcost	17174.55
gprofit	0.0679922
glprod	0.5991806
profit	0.4713401
lprod	423704.2
Tech1	0.1501173
Tech23	0.0643662
TTL_EMP	19.1985823
ProcProd	0.1525476
TTL_EMPBI	0.1573928
TRNG_EXPN	9048.87
TRNG_EXPBI	0.1230595
Tech2	0.0248044
Tech3	0.0448872
REVENUE	7322783.97
GRSPAYRLBI	0.2265399
TotaletrainBI	0.107076
TotaldtrainBI	0.0352456
SAL_EXPNBI	0.1209332
SAL_EXPN	120389.22
GRSPAYRL	1005715.46
Totaletrain	0.9275689
Cost/Employee	894.573867
Totaldtrain	0.498835

Table 49. Mean values for the forestry, mining, oil, and gas extraction industry

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	23	-1.937531	17	3.3813937	23-7-5-4
glprod	22	-0.178844	1	4.5623691	22-6-4-0-1
profit	23	0.0451772	21	3.4843912	23-7-5-21
lprod	30	164092.6	23	6332787.6	30-14-6-4-1

Table 50. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (forestry, mining, oil, and gas extraction industry).

State # (bin)	00000	00001	00010	00011	00100	00101	00110	00111	01000	01010
State # (dec)	0	1	2	3	4	5	6	7	8	10
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	3.0033	**-108.9**	-0.5592	-32.837	-2.5682	-3.4738	0.2039	3.1525	-0.0569	-5.835
glprod	0.2475	**0.4624**	0.0856	0.0922	0.0953	0.1876	0.0969	0.0904	0.2332	0.3303
Totalcost	0	0	0	0	0	0	0	0	64537	49769
profit	0.4158	0.2895	0.3099	0.4141	0.3374	0.3605	0.2363	0.5818	0.1433	0.2888
lprod	133096	260813	118762	260655	207525	197737	183092	227317	136526	108894
TTL_EMP	7.1636	11.245	9.4449	10.924	71.675	82.207	86.744	163.2	8.7392	5.5966
ProcProd	0	0	1	1	0	0	1	1	0	1
TRNG_EXPN	147.68	9968.6	138.86	11818	3532	85498	7192.8	156656	662.65	36.452
cost/employee	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**7384.8**	**8892.7**

State # (bin)	01100	01101	01110	01111	10000	10010	10100	10101	10110	10111
State # (dec)	12	13	14	15	16	18	20	21	22	23
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	1.5338	-0.0618	-0.5115	0.8592	-2.8709	3.9237	2.4868	-0.034	-0.0493	-2.028
glprod	-0.0052	0.1755	0.1013	0.003	0.145	0.1851	**-0.0083**	0.061	0.1072	0.0248
Totalcost	204964	248497	212262	442087	109730	12092	74661	149850	59851	151847
profit	0.1252	0.1022	0.3729	0.6233	0.1019	**0.1015**	**2.7068**	0.338	1.6856	0.3574
lprod	189539	275927	239015	254939	162154	**104547**	**360321**	247561	322794	257951
TTL_EMP	129.31	79.665	91.122	252.37	10.548	9.6952	111.82	106.37	102.27	237.52
ProcProd	0	0	1	1	0	1	0	0	1	1
TRNG_EXPN	13194	98700	6793.8	307532	543.71	221.71	11719	105195	8897.8	282710
cost/employee	**1585**	**3119.3**	**2329.4**	**1751.7**	**10403**	**1247.2**	**667.68**	**1408.7**	**585.23**	**639.3**

State # (bin)	11110	11111
State # (dec)	30	31
Variable	Mean	Mean
Gprofit	2.6201	**4.5731**
Glprod	0.1129	0.4285
Totalcost	434581	711676
Profit	0.1117	0.6056
Lprod	224204	223909
TTL_EMP	156	151.86
ProcProd	1	1
TRNG_EXPN	18083	143148
cost/employee	**2785.8**	**4686.5**

Table 51. State Means (Industry 02: labor intensive tertiary manufacturing)

Variable	Mean
Totalcost	20313.47
gprofit	-1.1764655
glprod	0.1780748
profit	0.4097183
lprod	152056.61
Tech1	0.1161381
Tech23	0.0907219
TTL_EMP	26.2032362
ProcProd	0.3903888
TTL_EMPBI	0.1987998
TRNG_EXPN	7870.45
TRNG_EXPBI	0.091022
Tech2	0.0381876
Tech3	0.0535364
REVENUE	5624149.15
GRSPAYRLBI	0.2564402
TotaletrainBI	0.0548816
TotaldtrainBI	0.0295874
SAL_EXPNBI	0.0832052
SAL_EXPN	71132.64
GRSPAYRL	878801.38
Totaletrain	1.5242315
Cost/Employee	775.227527
Totaldtrain	1.2430703

Table 52. Mean values for the labor intensive tertiary manufacturing industry

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	1	-108.8998	31	4.5730885	1-0-18
glprod	20	-0.008334	1	0.4623999	20-4-0-1
profit	18	0.1015109	20	2.7067863	18-22-20
lprod	18	104547.24	20	360321.3	18-22-20

Table 53. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (labor intensive tertiary manufacturing industry).

State # (bin)	00000	00001	00010	00100	00101	00110	00111	01000	01010	01100
State # (dec)	0	1	2	4	5	6	7	8	10	12
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	0.3988	-0.3371	1.1268	0.4259	-2.2718	**-13.834**	1.1243	-0.0266	-0.1946	14.894
glprod	0.2482	0.0033	0.1292	-0.0003	0.2873	0.1146	0.372	0.2136	**0.8754**	0.2016
Totalcost	0	0	0	0	0	0	0	65047	84732	731420
profit	0.2114	0.2174	0.2942	0.2159	0.3385	0.1438	0.2536	**0.1336**	0.2784	0.6123
lprod	161963	469329	142113	242957	342542	261916	341914	150969	189257	301178
TTL_EMP	11.794	14.104	13.617	118.65	163.86	123.29	136.25	15.31	16.999	145.16
ProcProd	0	0	1	0	0	1	1	0	1	0
TRNG_EXPN	757.37	22637	739.5	24238	238037	27345	214698	1722.3	1307.1	49132
cost/employee	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**4248.8**	**4984.5**	**5038.9**

State # (bin)	01101	01110	01111	10000	10010	10100	10101	10110	10111	11010
State # (dec)	13	14	15	16	18	20	21	22	23	26
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	1.7524	-0.1243	0.5075	0.2773	0.6042	0.0378	-0.1938	0.7902	-0.2061	0.3369
glprod	0.0464	0.1681	0.0805	0.0155	0.0023	0.187	0.0537	**-0.0285**	0.2959	0.1411
Totalcost	992683	815023	4E+06	29990	40679	560024	1E+06	97059	627016	113189
profit	0.238	0.1481	0.3183	0.3868	0.2564	0.3691	0.2631	0.5651	**1.7752**	0.6018
lprod	342142	252619	400231	252960	187512	264125	490014	262621	**526109**	**108447**
TTL_EMP	293.34	196.08	312.42	17.245	24.427	142.99	270.09	139.03	306.32	34.643
ProcProd	0	1	1	0	1	0	0	1	1	1
TRNG_EXPN	498857	41013	451578	1069.3	5120.6	28221	556814	37840	586564	1970.4
cost/employee	**3384.1**	**4156.6**	**12199**	**1739.1**	**1665.3**	**3916.6**	**4999.1**	**698.14**	**2046.9**	**3267.3**

State # (bin)	11100	11101	11110	11111
State # (dec)	28	29	30	31
Variable	Mean	Mean	Mean	Mean
gprofit	**84.783**	5.0032	-0.0929	3.2649
glprod	0.2249	0.257	0.7222	0.0721
Totalcost	500285	8E+06	966096	6E+06
profit	0.8838	0.3738	0.346	0.3644
lprod	312864	478625	206872	465052
TTL_EMP	196.21	560.35	190.89	533.26
ProcProd	0	0	1	1
TRNG_EXPN	30427	1E+06	55478	1E+06
cost/employee	**2549.7**	**14802**	**5060.9**	**10482**

Table 54. State Means (Industry 03: primary product manufacturing)

Variable	Mean
Totalcost	78392.44
gprofit	0.205446
glprod	0.1918688
profit	0.2593107
lprod	199594.95
Tech1	0.1454498
Tech23	0.1124969
TTL_EMP	47.2909588
ProcProd	0.3240486
TTL_EMPBI	0.2437244
TRNG_EXPN	29253.9
TRNG_EXPBI	0.1038002
Tech2	0.0554319
Tech3	0.0643167
REVENUE	13839165.42
GRSPAYRLBI	0.2555874
TotaletrainBI	0.048947
TotaldtrainBI	0.0722531
SAL_EXPNBI	0.1173482
SAL_EXPN	294017.08
GRSPAYRL	2224672.04
Totaletrain	3.4586544
Cost/Employee	1657.66231
Totaldtrain	1.0850201

Table 55. Mean values for the primary product manufacturing industry

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	6	-13.83427	28	84.783068	6-4-12-28
glprod	22	-0.028491	10	0.8754341	22-6-7-5
profit	8	0.1336037	23	1.7752156	8-0-1-5-7-23
lprod	26	108447.47	23	526109.38	26-18-22-23

Table 56. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (primary product manufacturing industry).

State # (bin)	00000	00001	00010	00011	00100	00101	00110	00111	01000	01010
State # (dec)	0	1	2	3	4	5	6	7	8	10
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	0.6392	-0.6345	-0.8317	-0.1569	0.7368	-0.491	0.0318	0.2298	-0.2503	**38.915**
glprod	0.1849	0.0931	0.1831	0.3176	-0.0095	**-0.0513**	0.0104	-0.0214	0.158	0.1183
Totalcost	0	0	0	0	0	0	0	0	83535	80369
profit	0.369	0.347	0.3481	0.3344	0.2481	0.2366	0.1992	0.2672	0.1216	0.1025
lprod	150529	378782	138025	**389661**	235854	262242	258480	270856	195193	**116482**
TTL_EMP	8.751	10.243	10.387	11.474	99.463	102.13	105.86	190.52	6.421	11.278
ProcProd	0	0	1	1	0	0	1	1	0	1
TRNG_EXPN	272.07	9666.7	312.66	22524	11233	86730	13139	206253	110.38	228.62
cost/employee	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**13010**	**7126.4**

State # (bin)	01100	01101	01110	01111	10000	10010	10100	10101	10110	10111
State # (dec)	12	13	14	15	16	18	20	21	22	23
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	0.5054	-0.4267	-0.1442	0.544	0.1749	2.0152	-0.2663	0.7855	**-1.109**	0.1109
glprod	0.0446	0.0516	0.3546	-0.0045	-0.0255	0.168	0.0433	0.0795	0.097	0.069
Totalcost	580173	158928	173367	598545	343991	7147.7	66588	591208	139493	185835
profit	0.1011	0.0567	**0.7248**	0.4559	0.5884	0.4353	0.2078	0.4579	0.2412	0.1726
lprod	244980	164829	172744	306930	128016	264785	214832	207575	290052	219705
TTL_EMP	92.787	110.22	86.745	259.43	11.699	9.5161	89.233	170.82	96.665	187.67
ProcProd	0	0	1	1	0	1	0	0	1	1
TRNG_EXPN	12049	120578	7037.2	347018	392.59	885.2	10200	153031	12183	243933
cost/employee	**6252.8**	**1441.9**	**1998.6**	**2307.1**	**29404**	**751.12**	**746.23**	**3461**	**1443.1**	**990.2**

State # (bin)	11100	11110	11111
State # (dec)	28	30	31
Variable	**Mean**	**Mean**	**Mean**
gprofit	-0.1576	0.0023	6.3155
glprod	-0.0021	-0.0054	**1.0932**
Totalcost	340971	434354	2E+06
profit	**0.0319**	0.5634	0.505
lprod	189896	245649	387065
TTL_EMP	142.83	105.03	426.9
ProcProd	0	1	1
TRNG_EXPN	20109	12494	434061
cost/employee	**2387.2**	**4135.7**	**3644**

Table 57. State Means (Industry 04: secondary product manufacturing)

Variable	Mean
Totalcost	65114.09
gprofit	0.8723308
glprod	0.1513107
profit	0.3486521
lprod	193687.29
Tech1	0.1624483
Tech23	0.1375902
TTL_EMP	32.6905815
ProcProd	0.3679806
TTL_EMPBI	0.2174042
TRNG_EXPN	13029.54
TRNG_EXPBI	0.1636608
Tech2	0.1038033
Tech3	0.048458
REVENUE	8101838.2
GRSPAYRLBI	0.3667184
TotaletrainBI	0.1048559
TotaldtrainBI	0.025401
SAL_EXPNBI	0.1468035
SAL_EXPN	129130.54
GRSPAYRL	1424827.09
Totaletrain	2.8506228
Cost/Employee	1991.83028
Totaldtrain	2.7505371

Table 58. Mean values for the secondary product manufacturing industry

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	22	0	10	0	22-18
glprod	5	-1.10905	31	38.914752	5-7-23-31
profit	28	0	14	1555627.3	28-20-22-18
lprod	10	0.0319135	3	0.7247685	10-2-3

Table 59. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (secondary product manufacturing industry).

State # (bin)	00000	00001	00010	00011	00100	00101	00110	00111	01000	01010
State # (dec)	0	1	2	3	4	5	6	7	8	10
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	-1.4632	1.4414	-1.1623	-5.1173	-0.4366	-0.52	0.4186	-0.3827	**-5.1725**	-0.6054
glprod	0.0876	0.0652	0.0937	0.0634	0.0112	0.062	0.0054	0.0471	**-0.0353**	0.1341
Totalcost	0	0	0	0	0	0	0	0	93201	120347
profit	0.3318	1.1839	1.3161	0.1938	0.2084	0.1578	0.3137	0.4957	0.2309	0.6322
lprod	138984	**308650**	221622	224943	180745	259688	175408	205257	112997	138657
TTL_EMP	9.3805	17.207	12.271	10.341	84.456	100.14	126.37	260.37	16.927	10.997
ProcProd	0	0	1	1	0	0	1	1	0	1
TRNG_EXPN	175.4	15805	795.45	14993	10253	82508	28676	252112	226.56	347.99
cost/employee	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**5506.2**	**10943**

State # (bin)	01100	01110	01111	10000	10010	10100	10101	10110	10111	11010
State # (dec)	12	14	15	16	18	20	21	22	23	26
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	4.5687	0.6948	0.7216	0.3397	2.5046	0.5759	**4.9699**	-0.4612	0.0926	-0.137
glprod	0.1473	0.1765	**0.522**	0.1395	0.5031	-0.0089	0.0494	-0.0234	0.0032	0.2219
Totalcost	1E+06	790060	480901	11446	18959	161998	73484	305749	194640	151092
profit	0.1374	0.2954	0.2778	0.215	**1.9442**	0.2056	0.196	0.2473	0.4404	0.3018
lprod	202957	152200	127025	**108137**	234743	135396	228198	153525	152915	126008
TTL_EMP	128.58	96.539	274.04	11.518	13.335	142.62	139.42	138.11	281.63	13.535
ProcProd	0	1	1	0	1	0	0	1	1	1
TRNG_EXPN	16714	21819	624717	609.08	2169.4	25715	120551	25949	676003	2550.6
cost/employee	**8242.6**	**8183.9**	**1754.9**	**993.71**	**1421.7**	**1135.8**	**527.06**	**2213.9**	**691.13**	**11163**

State # (bin)	11100	11110	11111
State # (dec)	28	30	31
Variable	**Mean**	**Mean**	**Mean**
gprofit	0.3836	-1.5827	4.6938
glprod	-0.0086	0.0566	0.0038
Totalcost	194096	1E+06	445214
profit	**0.0983**	0.1906	0.1802
lprod	114364	122946	140262
TTL_EMP	145.48	148.39	162.19
ProcProd	0	1	1
TRNG_EXPN	10505	23336	181605
cost/employee	**1334.2**	**7300.8**	**2745**

Table 60. State Means (Industry 05: capital intensive tertiary manufacturing)

Variable	Mean
Totalcost	49943.77
gprofit	-0.8008177
glprod	0.1115811
profit	0.6890783
lprod	174790.15
Tech1	0.2019094
Tech23	0.1214626
TTL_EMP	33.7459309
ProcProd	0.4151902
TTL_EMPBI	0.1914646
TRNG_EXPN	16454.57
TRNG_EXPBI	0.1420573
Tech2	0.0612785
Tech3	0.0677595
REVENUE	6949969.2
GRSPAYRLBI	0.3006934
TotaletrainBI	0.0913283
TotaldtrainBI	0.066077
SAL_EXPNBI	0.0853904
SAL_EXPN	142834.56
GRSPAYRL	1518446.55
Totaletrain	2.7721523
Cost/Employee	1479.99384
Totaldtrain	1.539144

Table 61. Mean values for the capital intensive tertiary manufacturing industry

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	8	-5.172527	21	4.9698705	8-16-20-21
glprod	8	-0.035345	15	0.5220348	8-2-3-7-15
profit	28	0.0982746	18	1.9441698	28-20-16-18
lprod	16	108136.51	1	308650.25	16-0-1

Table 62. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (capital intensive tertiary manufacturing industry).

State # (bin)	00000	00001	00010	00011	00100	00101	00110	00111	01000	01100
State # (dec)	0	1	2	3	4	5	6	7	8	12
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-0.0982	-7.9217	-1.1611	6.8835	1.568	**-13.774**	20.32	1.2301	-3.1724	2.5471
glprod	0.376	0.3037	0.971	0.2263	0.1004	0.2397	0.6666	0.0393	**-0.0964**	0.493
Totalcost	0	0	0	0	0	0	0	0	81301	77205
profit	0.3717	**0.065**	0.2628	0.184	0.1501	0.1763	0.7988	0.6324	0.2595	0.2475
lprod	201092	340729	182257	303666	194500	196342	239794	182581	**88470**	153114
TTL_EMP	3.4867	4.3908	4.079	5.4319	24.113	27.84	22.41	23.362	4.231	28.195
ProcProd	0	0	1	1	0	0	1	1	0	0
TRNG_EXPN	29.982	4528.8	132.7	4050.8	707.86	20754	1227.8	24443	7.7801	1125.7
cost/employee	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**19215**	**2738.3**

State # (bin)	01110	01111	10000	10010	10100	10101	10110	10111	11111
State # (dec)	14	15	16	18	20	21	22	23	31
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	0.5078	**40.061**	0.1959	-0.3821	-0.7956	-0.4836	0.9717	-1.5513	-0.1821
glprod	0.3677	1.0627	-0.0434	0.8277	0.2757	0.2891	0.3965	0.4468	**1.9779**
Totalcost	20168	18569	5950.4	3551.6	23492	19899	55844	57476	341374
profit	0.1554	**0.8898**	0.186	0.1685	0.2027	0.5556	0.1502	0.6281	0.3343
lprod	218019	128904	144076	186228	201614	188660	121121	167567	**667566**
TTL_EMP	30.312	18.494	4.8068	4.8835	25.701	27.559	28.997	24.1	34.696
ProcProd	1	1	0	1	0	0	1	1	1
TRNG_EXPN	2724.2	11288	112.27	351.89	783.39	15135	1595.7	36977	19820
cost/employee	**665.35**	**1004.1**	**1237.9**	**727.26**	**914.04**	**722.05**	**1925.8**	**2384.9**	**9839.1**

Table 63. State Means (Industry 06: construction)

Variable	Mean
Totalcost	5110.68
gprofit	0.0090642
glprod	0.3882217
profit	0.3076353
lprod	203469.48
Tech1	0.1156625
Tech23	0.044308
TTL_EMP	9.0040774
ProcProd	0.2173353
TTL_EMPBI	0.2438741
TRNG_EXPN	2144.35
TRNG_EXPBI	0.1502073
Tech2	0.0142102
Tech3	0.0300978
REVENUE	1847748.97
GRSPAYRLBI	0.3113559
TotaletrainBI	0.059222
TotaldtrainBI	0.01647
SAL_EXPNBI	0.1792062
SAL_EXPN	23683.8
GRSPAYRL	398406.7
Totaletrain	0.3787268
Cost/Employee	567.596187
Totaldtrain	1.844265

Table 64. Mean values for the capital intensive construction industry

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	5	0	15	0	5-7-15
glprod	8	-13.77	31	40.061	8-0-2-3-7-15
profit	1	0	15	341374	1-5-7-15
lprod	8	0.065	31	0.8898	8-0-2-3-7-15

Table 65. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (construction industry).

State # (bin)	00000	00001	00010	00011	00100	00101	00110	00111	01000	01100
State # (dec)	0	1	2	3	4	5	6	7	8	12
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	0.112	-0.6512	2.8716	-1.2079	0.8263	6.7144	-1.3251	1.1111	-1.6208	-1.9056
glprod	0.1823	0.185	0.1958	0.0923	0.1351	0.1253	**0.4093**	0.0504	0.018	0.1362
Totalcost	0	0	0	0	0	0	0	0	72049	182774
profit	0.4872	0.8538	0.8584	3.2391	0.4858	0.4195	0.938	1.5484	0.098	**-0.0109**
lprod	305154	343578	448028	**815137**	287895	400043	277368	405899	189570	**113221**
TTL_EMP	5.5669	6.4047	6.8687	6.9947	38.324	55.518	45.836	63.126	5.9773	40.722
ProcProd	0	0	1	1	0	0	1	1	0	0
TRNG_EXPN	241.69	7732	362.91	7151.8	4754.9	60217	7186.9	275315	46.135	4155.4
cost/employee	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**12054**	**4488.4**

State # (bin)	01110	01111	10000	10010	10011	10100	10101	10110	10111	11100
State # (dec)	14	15	16	18	19	20	21	22	23	28
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	0.0463	**-3.4028**	-0.7168	2.0419	-0.4371	-0.4446	0.6414	0.0998	-0.4629	1.1522
glprod	0.0266	-0.0724	0.0137	0.1029	-0.0777	0.0457	-0.0012	0.2234	-0.0347	-0.1715
Totalcost	117602	504672	72377	998637	4E+06	50841	375893	166813	614840	150221
profit	0.398	0.1445	0.5476	0.5384	2.7126	0.1503	0.9135	1.2596	1.7676	0.3145
lprod	365524	360048	268480	302970	533834	145320	315579	324072	590276	380286
TTL_EMP	70.658	140.96	7.7391	7.1824	9.0097	48.234	53.652	53.297	62.612	47.363
ProcProd	1	1	0	1	1	0	0	1	1	0
TRNG_EXPN	10287	110230	506.47	92.314	10900	7698.9	67610	9087.4	95539	4472.8
cost/employee	**1664.4**	3580.3	9352.1	139039	468883	1054	7006.1	3129.9	9819.9	3171.7

State # (bin)	11110	11111
State # (dec)	30	31
Variable	Mean	Mean
gprofit	-0.9179	**492.22**
glprod	**-0.1832**	-0.0238
Totalcost	180439	491613
profit	0.5685	**6.0864**
lprod	560733	430204
TTL_EMP	95.265	74.663
ProcProd	1	1
TRNG_EXPN	15153	79716
cost/employee	**1894.1**	**6584.4**

Table 66. State Means (Industry 07: transportation, warehousing, wholesale)

Variable	Mean
Totalcost	102730.42
gprofit	0.8201586
glprod	0.1653674
profit	0.6571977
lprod	328118.68
Tech1	0.152545
Tech23	0.0451876
TTL_EMP	15.3283999
ProcProd	0.2736412
TTL_EMPBI	0.2279718
TRNG_EXPN	7428.75
TRNG_EXPBI	0.0972978
Tech2	0.0258361
Tech3	0.020623
REVENUE	5461857.33
GRSPAYRLBI	0.3006274
TotaletrainBI	0.0796637
TotaldtrainBI	0.0454046
SAL_EXPNBI	0.1858586
SAL_EXPN	50033.04
GRSPAYRL	657782.3
Totaletrain	1.4291671
Cost/Employee	6701.96633
Totaldtrain	0.5899582

Table 67. Mean values for the transportation, warehousing, wholesale industry

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	15	0	31	0	15-31
glprod	30	-3.403	6	492.22	30-22-6
profit	12	0	31	4E+06	12-14-30-31
lprod	12	-0.011	3	6.0864	12-14-15-7-3

Table 68. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (transportation, warehousing, wholesale industry).

State # (bin)	00000	00001	00010	00011	00100	00101	00110	00111	01000	01010
State # (dec)	0	1	2	3	4	5	6	7	8	10
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	1.6679	**-5.6381**	0.8806	-1.0792	-1.0159	-1.1618	**55.294**	1.0247	-1.2081	0.3341
glprod	0.1694	**0.8666**	0.157	0.2006	0.1149	0.0558	0.2179	0.1833	0.2264	0.0301
Totalcost	0	0	0	0	0	0	0	0	28941	52231
profit	0.2826	0.3488	0.1758	0.0407	0.2952	0.0948	0.286	0.3271	0.1631	0.2256
lprod	139628	233313	159331	328611	166821	207239	222781	362605	215255	**102033**
TTL_EMP	7.2143	11.522	9.355	12.406	58.866	93.007	75.557	80.617	8.1495	8.2855
ProcProd	0	0	1	1	0	0	1	1	0	1
TRNG_EXPN	529.7	17297	1009.8	13984	8683.5	158214	12147	167337	2056.7	1598.5
cost/employee	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**3551.2**	**6303.9**

State # (bin)	10000	10001	10010	10100	10101	10110	10111	11110
State # (dec)	16	17	18	20	21	22	23	30
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-0.745	-3.038	-0.3562	-0.8484	-0.0165	-0.1475	0.4755	-1.9637
glprod	0.2866	0.1425	0.1364	0.4943	0.0395	0.0315	0.2833	**-0.1265**
Totalcost	10479	6529.8	67667	176002	1E+06	214435	261764	1E+06
profit	0.1338	**0.0046**	0.1552	0.1343	0.0239	0.2491	**0.5801**	0.407
lprod	183713	382945	196301	167707	312112	137921	**578366**	176595
TTL_EMP	7.6809	4.3541	9.9839	73.495	102.68	77.53	101.13	128.81
ProcProd	0	0	1	0	0	1	1	1
TRNG_EXPN	868.79	10167	1788.7	4058.7	207989	14492	140820	12755
cost/employee	**1364.3**	**1499.7**	**6777.5**	**2394.7**	**12428**	**2765.8**	**2588.4**	**10956**

Table 69. State Means (Industry 08: communication and other utilities)

Variable	Mean
Totalcost	24060.43
gprofit	2.8209444
glprod	0.210033
profit	0.2572169
lprod	184050.92
Tech1	0.1586085
Tech23	0.0460851
TTL_EMP	22.2937797
ProcProd	0.2820466
TTL_EMPBI	0.219265
TRNG_EXPN	12066.28
TRNG_EXPBI	0.1560306
Tech2	0.0243877
Tech3	0.0219261
REVENUE	6242991.26
GRSPAYRLBI	0.2906223
TotaletrainBI	0.0610047
TotaldtrainBI	0.061277
SAL_EXPNBI	0.2117729
SAL_EXPN	88286.58
GRSPAYRL	936368.11
Totaletrain	1.7225199
Cost/Employee	1079.24409
Totaldtrain	0.8388859

Table 70. Mean values for the communication and other utilities industry

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	1	0	6	0	1-0-2-6
glprod	30	-5.638124	1	55.294227	30-28-24-16-0-1
profit	17	0	23	1411230.6	17-1-3-7-23
lprod	10	0.0046206	23	0.5800555	10-2-3-7-23

Table 71. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (communication and other utilities industry).

State # (bin)	00000	00001	00010	00011	00100	00101	00110	00111	01000	01100
State # (dec)	0	1	2	3	4	5	6	7	8	12
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-0.8077	-4.3364	0.1526	1.1503	7.7925	1.4794	-0.3743	-0.0326	0.8782	0.7443
glprod	0.4043	0.0536	0.1101	0.1447	0.119	0.0893	0.1948	0.1691	0.2066	**-0.2669**
Totalcost	0	0	0	0	0	0	0	0	15575	21985
profit	0.5202	0.2351	0.6011	0.3082	0.3724	0.7504	0.4078	1.214	0.9549	**0.1846**
lprod	128917	134937	122023	168106	94077	177594	89151	190853	95944	**68648**
TTL_EMP	4.4904	4.8227	5.652	5.5691	31.048	44.665	35.702	56.372	5.9128	36.699
ProcProd	0	0	1	1	0	0	1	1	0	0
TRNG_EXPN	16.499	3722.8	16.94	3589.2	464.34	20062	704.41	23707	-3	396.8
cost/employee	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**2634.1**	**599.05**

State # (bin)	01110	01111	10000	10010	10011	10100	10101	10110	10111	11110
State # (dec)	14	15	16	18	19	20	21	22	23	30
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	7.3326	-0.3631	0.4289	**-23.131**	-2.1918	0.1988	1.7632	**12.975**	1.5347	0.5885
glprod	0.2336	0.0719	0.1023	**0.5457**	0.262	-0.0229	0.1477	-0.0744	0.0302	-0.0587
Totalcost	24319	187576	15954	11783	12502	40478	20609	12546	52833	132065
profit	**1.5505**	0.5643	1.2884	0.5175	1.1393	0.2834	1.18	0.2788	0.2641	0.4513
lprod	169227	**291554**	204733	257088	237013	102018	206256	86020	126703	109445
TTL_EMP	53.614	107.96	5.7745	5.3033	5.8405	51.981	48.726	36.766	56.776	67.958
ProcProd	1	1	0	1	1	0	0	1	1	1
TRNG_EXPN	1930.1	39960	9.4514	12.097	4461.4	1574.2	20419	1533.3	29372	3143.5
cost/employee	**453.59**	**1737.4**	**2762.8**	**2221.9**	**2140.6**	**778.7**	**422.95**	**341.25**	**930.54**	**1943.3**

State # (bin)	11111
State # (dec)	31
Variable	Mean
gprofit	- 0.1287
glprod	0.0628
Totalcost	136573
profit	0.3287
lprod	158156
TTL_EMP	52.168
ProcProd	1
TRNG_EXPN	19514
cost/employee	**2617.9**

Table 72. State Means (Industry 09: retail trade and consumer services)

Variable	Mean
Totalcost	2860.29
gprofit	0.1080634
glprod	0.2636376
profit	0.5461931
lprod	131032.42
Tech1	0.0906688
Tech23	0.0474268
TTL_EMP	12.2495961
ProcProd	0.3364199
TTL_EMPBI	0.2178467
TRNG_EXPN	1593.12
TRNG_EXPBI	0.1364009
Tech2	0.0366953
Tech3	0.0115299
REVENUE	1527873.11
GRSPAYRLBI	0.3512274
TotaletrainBI	0.0427187
TotaldtrainBI	0.027985
SAL_EXPNBI	0.1592855
SAL_EXPN	11917.75
GRSPAYRL	225081.01
Totaletrain	0.9019645
Cost/Employee	233.50076
Totaldtrain	0.2929747

Table 73. Mean values for the retail trade and consumer services industry

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	18	0	22	0	2-6-22
glprod	12	-23.13118	18	12.975403	12-4-0
profit	12	0	14	187576.09	12-4-6-14
lprod	12	0.1846166	15	1.5504824	12-4-5-21

Table 74. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (retail trade and consumer services industry).

State # (bin)	00000	00001	00010	00011	00100	00101	00110	00111	01110	01111
State # (dec)	0	1	2	3	4	5	6	7	14	15
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	-0.7453	-0.4207	1.4993	-0.5946	**-1.5183**	-0.3982	5.1616	1.9087	-0.5868	-0.6439
glprod	0.193	0.0703	0.0917	0.9942	0.0559	0.2619	0.0919	0.1021	**-0.0551**	**12.019**
Totalcost	0	0	0	0	0	0	0	0	24165	157656
profit	0.6703	**0.2721**	0.6327	0.5771	0.54	0.4435	0.6606	0.6025	0.789	0.3996
lprod	188128	311123	146322	305086	173625	188233	188264	206578	190326	192585
TTL_EMP	4.6585	6.0549	6.1147	6.3983	28.711	45.684	32.809	61.607	33.197	91.782
ProcProd	0	0	1	1	0	0	1	1	1	1
TRNG_EXPN	257.21	5157.2	560.79	11655	3921.1	49592	6297.5	61537	9041.2	115392
cost/employee	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**727.93**	**1717.7**

State # (bin)	10000	10001	10010	10011	10100	10101	10110	10111	11110	11111
State # (dec)	16	17	18	19	20	21	22	23	30	31
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	-1.022	4.0086	**247.29**	-1.254	1.7567	2.1932	0.2038	0.4551	7.8738	0.2146
glprod	0.1081	0.0034	0.1888	0.1567	0.0172	0.0656	0.0762	0.0986	0.1556	0.4329
Totalcost	9134.4	218422	274266	6E+06	360948	195687	73984	97622	211784	121664
profit	1.0617	0.5676	0.62	1.4852	0.3696	0.9102	0.7953	1.0395	**1.486**	0.8232
lprod	225977	**330695**	**129455**	180139	159568	184427	163185	191089	265266	316050
TTL_EMP	4.3456	6.2002	6.7317	6.7836	28.064	47.358	34.165	39.082	81.718	97.165
ProcProd	0	0	1	1	0	0	1	1	1	1
TRNG_EXPN	489.7	8660.8	870.55	8341.2	5186.4	45633	7257	47041	15404	88006
cost/employee	**2102**	**35228**	**40742**	**847602**	**12862**	**4132.1**	**2165.5**	**2497.9**	**2591.7**	**1252.1**

Table 75. State Means (Industry 10: finance and insurance)

Variable	Mean
Totalcost	210443.42
gprofit	15.1607466
glprod	0.2057358
profit	0.6717671
lprod	191178.7
Tech1	0.2556259
Tech23	0.0408521
TTL_EMP	14.3571479
ProcProd	0.4768831
TTL_EMPBI	0.2817075
TRNG_EXPN	7144.33
TRNG_EXPBI	0.2485591
Tech2	0.0217629
Tech3	0.0190891
REVENUE	3748252.14
GRSPAYRLBI	0.2416018
TotaletrainBI	0.1627919
TotaldtrainBI	0.0820827
SAL_EXPNBI	0.2451302
SAL_EXPN	54321.46
GRSPAYRL	628469.98
Totaletrain	2.5223413
Cost/Employee	14657.7455
Totaldtrain	0.8028993

Table 76. Mean values for the finance and insurance industry

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	4	-1.518344	18	247.29392	4-6-14-30
glprod	14	-0.055135	15	12.018758	14-15
profit	1	0.2721279	30	1.4859543	1-3-7-6-14-31
lprod	18	129455.25	17	330694.85	18-22-23-31

Table 77. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (finance and insurance industry).

State # (bin)	00000	00001	00010	00100	00101	00110	00111	10000	10001	10010
State # (dec)	0	1	2	4	5	6	7	16	17	18
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	-2.6872	**-5.8078**	4.5954	0.1021	-3.0173	2.7659	-2.531	-1.364	11.597	0.543
glprod	0.2966	0.1275	0.1588	0.1007	0.064	0.0461	0.019	-0.0068	0.3073	0.2039
Totalcost	0	0	0	0	0	0	0	15669	10961	6740.5
profit	0.3659	0.153	0.3337	0.3898	0.2728	**0.6986**	0.5306	0.2458	0.4286	0.3782
lprod	201089	275141	299525	**144962**	224822	203744	**336319**	322356	147720	252453
TTL_EMP	3.0973	4.3367	2.9432	15.347	30.021	16.848	24.301	3.6795	3.3825	3.7412
ProcProd	0	0	1	0	0	1	1	0	0	1
TRNG_EXPN	13.157	2121.2	2.5044	295.21	12940	445	11540	21.826	3658.7	-2.5848
cost/employee	0	0	0	0	0	0	0	4258.4	3240.7	1801.7

State # (bin)	10100	10101	10110	10111	11111
State # (dec)	20	21	22	23	31
Variable	Mean	Mean	Mean	Mean	Mean
gprofit	**38.924**	0.6214	0.6855	-5.0279	-0.0207
glprod	0.0771	0.1625	**0.4759**	0.1605	**-0.1377**
Totalcost	11743	19128	179377	19880	100070
profit	**0.0586**	0.1498	0.2613	0.4271	0.4616
lprod	232377	306265	181352	317818	268986
TTL_EMP	14.48	21.648	15.485	23.821	27.11
ProcProd	0	0	1	1	1
TRNG_EXPN	72.725	9689.9	378.3	12288	18256
cost/employee	810.99	883.56	11584	834.57	3691.2

Table 78. State Means (Industry 11: real estate, rental and leasing operations)

Variable	Mean
Totalcost	5559.92
gprofit	-0.5239633
glprod	0.2275001
profit	0.3426452
lprod	217015.45
Tech1	0.1496938
Tech23	0.0343001
TTL_EMP	6.5575383
ProcProd	0.1987047
TTL_EMPBI	0.2255495
TRNG_EXPN	975.4369479
TRNG_EXPBI	0.1457346
Tech2	0.0278639
Tech3	0.007801
REVENUE	1474056.78
GRSPAYRLBI	0.2575111
TotaletrainBI	0.0790351
TotaldtrainBI	0.0341463
SAL_EXPNBI	0.1429238
SAL_EXPN	9392.26
GRSPAYRL	219414.01
Totaletrain	0.7460291
Cost/Employee	847.8669503
Totaldtrain	0.5767165

Table 79. Mean values for the real estate, rental and leasing operations industry

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	1	-5.80781	20	38.923805	1-0-4-20
glprod	31	-0.13772	22	0.4759314	31-23-21-5-0
profit	20	0.0586435	6	0.6985946	20-4-6
lprod	4	144961.82	7	336318.8	4-5-7

Table 80. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (real estate, rental and leasing operations industry).

State # (bin)	00000	00001	00010	00011	00100	00101	00110	00111	01110	10000
State #	0	1	2	3	4	5	6	7	14	16
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	1.9286	-0.803	0.4795	-0.3741	0.8463	1.786	0.354	-0.4629	-1.0432	-0.1655
glprod	0.2834	0.0913	0.1606	0.0797	0.2961	0.2179	-0.0098	0.255	-0.0558	0.5356
Totalcost	0	0	0	0	0	0	0	0	169287	11661
profit	0.7884	0.487	0.6458	0.2074	0.5648	0.1906	0.5734	0.2612	0.3404	0.6094
lprod	151853	194103	171682	135261	**131685**	179189	164400	223068	155344	147137
TTL_EMP	3.6476	6.5171	5.6336	7.8046	37.997	64.664	65.957	95.554	191.27	4.8983
ProcProd	0	0	1	1	0	0	1	1	1	0
TRNG_EXPN	120.6	7174.8	269.21	4533.1	3169.6	84618	8934.1	113624	32201	155.37
cost/employee	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**885.09**	**2380.7**

State # (bin)	10001	10010	10011	10100	10101	10110	10111	11110	11111
State #	17	18	19	20	21	22	23	30	31
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-0.841	**15.685**	0.2923	-0.4659	2.0219	**-2.6582**	13.607	-2.138	2.6799
glprod	0.2326	0.0461	**1.4922**	0.4491	0.1032	**-0.1744**	0.2908	0.1464	0.0978
Totalcost	10980	8167.4	23176	202589	63471	462522	484127	2E+06	194307
profit	0.2737	0.3777	0.5442	**2.9314**	0.2065	0.4225	**0.1342**	0.1998	0.1621
lprod	141527	238699	152722	**339017**	233730	198458	210543	323410	265333
TTL_EMP	5.7462	4.9419	6.4665	85.721	39.13	46.341	147.55	70.778	92.227
ProcProd	0	1	1	0	0	1	1	1	1
TRNG_EXPN	5941.5	664.53	6802.4	12521	62329	4546.2	240829	4544	101606
cost/employee	**1910.8**	**1652.7**	**3584**	**2363.4**	**1622**	**9980.8**	**3281**	**25421**	**2106.8**

Table 81. State Means (Industry 12: business services)

Variable	Mean
Totalcost	30143.83
gprofit	1.7369727
glprod	0.2686527
profit	0.6701564
lprod	160764.8
Tech1	0.1927976
Tech23	0.0381547
TTL_EMP	13.262914
ProcProd	0.2397689
TTL_EMPBI	0.16914
TRNG_EXPN	5581.61
TRNG_EXPBI	0.1276502
Tech2	0.0257008
Tech3	0.0125082
REVENUE	2635358.03
GRSPAYRLBI	0.2504595
TotaletrainBI	0.1092265
TotaldtrainBI	0.041483
SAL_EXPNBI	0.1451985
SAL_EXPN	36766.98
GRSPAYRL	582633.48
Totaletrain	1.3672076
Cost/Employee	2272.79088
Totaldtrain	0.4533678

Table 82. Mean values for the business services industry

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	22	-2.658246	18	15.685049	22-18
glprod	22	-0.174406	19	1.4921825	22-5-2-3-19
profit	23	0.1341839	20	2.9314349	32-21-20
lprod	4	131684.84	20	339017.05	4-5-21-20

Table 83. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (business services industry).

State # (bin)	00000	00001	00010	00011	00100	00101	00110	00111	10000	10001
State # (dec)	0	1	2	3	4	5	6	7	16	17
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-0.0464	-0.1497	0.0429	-0.5234	**11.053**	-0.4037	-0.7283	0.253	0.5319	0.2982
glprod	0.1211	0.0631	0.2362	0.147	-0.0419	0.017	0.0299	**-0.0638**	0.2261	0.0861
Totalcost	0	0	0	0	0	0	0	0	3141.5	7533.5
profit	0.9404	0.2698	0.6011	0.3755	0.378	0.2113	0.2056	**0.1112**	0.8386	0.6743
lprod	108436	90272	92556	104061	**64460**	69240	72334	94978	114117	**124189**
TTL_EMP	3.2933	4.1689	4.1554	3.0341	27.984	26.256	31.475	62.508	3.4183	3.3348
ProcProd	0	0	1	1	0	0	1	1	0	0
TRNG_EXPN	30.171	2641.5	36.272	2966.9	945.19	15746	2296.8	33982	70.073	2841
cost/employee	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**919.02**	**2259**

State # (bin)	10010	10011	10100	10110	10111
State # (dec)	18	19	20	22	23
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	2.7118	**-43.263**	-0.1337	-0.2532	1.5785
glprod	**0.4455**	0.2479	0.048	0.0852	0.1438
Totalcost	5782	11819	24710	15669	19745
profit	**0.948**	0.3518	0.5355	0.4682	0.3214
lprod	120393	118539	80143	67201	89042
TTL_EMP	2.6675	3.8442	33.387	57.773	23.687
ProcProd	1	1	0	1	1
TRNG_EXPN	82.507	6158.5	2324	2396.1	21775
cost/employee	**2167.6**	**3074.4**	**740.1**	**271.22**	**833.58**

Table 84. State Means (Industry 13: education and health services)

Variable	Mean
Totalcost	3074.28
gprofit	0.265391
glprod	0.1198054
profit	0.7304355
lprod	100857.97
Tech1	0.1626919
Tech23	0.0504228
TTL_EMP	8.7062098
ProcProd	0.2366073
TTL_EMPBI	0.1868173
TRNG_EXPN	1553.72
TRNG_EXPBI	0.1568449
Tech2	0.0301413
Tech3	0.0202815
REVENUE	659501.5
GRSPAYRLBI	0.4214026
TotaletrainBI	0.113845
TotaldtrainBI	0.0559592
SAL_EXPNBI	0.1401304
SAL_EXPN	11273.03
GRSPAYRL	222308.96
Totaletrain	0.698527
Cost/Employee	353.113475
Totaldtrain	0.2882164

Table 85. Mean values for the education and health services industry

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	19	-43.26308	4	11.052737	19-3-2-0-4
glprod	7	-0.063764	18	0.4455318	7-3-2
profit	7	0.111232	18	0.9480429	7-3-2-0
lprod	4	64459.73	17	124189.43	4-0

Table 86. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (education and health services industry).

State # (bin)	00000	00001	00010	00011	00100	00101	00110	00111	01100	01110
State # (dec)	0	1	2	3	4	5	6	7	12	14
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	-0.2477	0.9389	-0.4004	-0.7948	**8.6593**	-0.0745	1.923	0.7073	-0.1131	-0.0889
glprod	0.4092	0.0369	0.2575	0.2891	0.064	0.0225	0.178	0.0744	0.0944	-0.0311
Totalcost	0	0	0	0	0	0	0	0	62396	237061
profit	0.4846	0.5618	0.8332	**1.7133**	0.2863	0.3557	0.3113	0.3049	0.3414	0.4561
lprod	182678	241028	181270	240133	**109722**	170682	160607	229105	144841	141832
TTL_EMP	5.7587	8.1133	8.1489	7.5069	104.87	152.37	128.52	207.14	232.07	116.62
ProcProd	0	0	1	1	0	0	1	1	0	1
TRNG_EXPN	161.7	10475	437.35	12506	9245.1	162836	11352	188662	23526	11659
cost/employee	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**268.87**	**2032.8**

State # (bin)	10000	10010	10100	10101	10110	10111	11110	11111
State # (dec)	16	18	20	21	22	23	30	31
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	-1.363	**-6.2027**	-0.4258	-0.4682	0.0685	-0.1613	-0.4256	-0.2994
glprod	0.0142	0.4437	0.08	**0.4667**	**-0.0704**	0.1862	0.1177	0.3188
Totalcost	11569	21442	85391	215640	210896	892576	987782	897804
profit	0.7814	0.8383	0.3076	0.3527	**0.1185**	0.2826	0.1367	0.198
lprod	199692	138691	127838	139221	142304	195532	141648	**248816**
TTL_EMP	4.6247	8.3237	108.6	180.88	98.802	255.83	192.11	331.47
ProcProd	0	1	0	0	1	1	1	1
TRNG_EXPN	101.45	728.1	15007	236617	14020	223425	38664	258358
cost/employee	**2501.6**	**2576.1**	**786.27**	**1192.2**	**2134.5**	**3488.9**	**5141.9**	**2708.6**

Table 87. State Means (Industry 14: information and cultural industries)

Variable	Mean
Totalcost	32875.86
gprofit	-0.2178953
glprod	0.2741761
profit	0.6162616
lprod	177324.71
Tech1	0.2074592
Tech23	0.0672916
TTL_EMP	28.6625823
ProcProd	0.4336903
TTL_EMPBI	0.1689893
TRNG_EXPN	11035.53
TRNG_EXPBI	0.1537179
Tech2	0.0456477
Tech3	0.0274983
REVENUE	5506193.5
GRSPAYRLBI	0.2190605
TotaletrainBI	0.1091272
TotaldtrainBI	0.0415951
SAL_EXPNBI	0.1063834
SAL_EXPN	122544.17
GRSPAYRL	1356308.53
Totaletrain	2.70813
Cost/Employee	1146.99575
Totaldtrain	1.0688084

Table 88. Mean values for the information and cultural industries

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	18	-6.202745	4	8.6593206	18-2-5-4
glprod	22	-0.070392	21	0.4667498	22-20-21
profit	22	0.1185101	3	1.7132772	22-6-7-3
lprod	4	109722.26	31	248816.04	4-6-7-15-31

Table 89. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (information and cultural industries).

State # (bin)	0000	0001	0010	0011	0100	0101	0110	0111	1000	1001
State # (dec)	0	1	2	3	4	5	6	7	8	9
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	7.1082	-5.3649	2.9318	5.8969	**-139.45**	5.497	**1512.8**	-0.8142	78.803	3.1272
glprod	0.8906	**0.6565**	0.7732	**4.4286**	1.2305	0.8684	1.5398	1.1573	1.5826	0.8303
Totalcost	34622	9151.6	16833	6565.2	52352	25798	37910	21757	36027	16831
profit	0.5477	0.6219	0.36	1.1043	0.5534	0.5304	1.1694	**0.1806**	0.6085	0.2984
lprod	171115	**149844**	175138	**402845**	191528	212035	224166	323961	218038	169996
TTL_EMP	17.911	20.01	27.652	21.17	26.455	24.675	29.663	15.352	35.848	24.763
GRSPAYRL	625090	735936	1E+06	889577	1E+06	890899	1E+06	718888	2E+06	983324
cost/employee	**1933**	**457.35**	**608.73**	**310.12**	**1978.9**	**1045.5**	**1278**	**1417.2**	**1005**	**679.7**

State # (bin)	1010	1011	1100	1101	1110	1111
State # (dec)	10	11	12	13	14	15
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	3.9048	8.5486	24.297	3.8514	4.5739	110.87
glprod	1.1327	2.7313	1.6324	0.6858	2.0343	0.9408
Totalcost	38820	71706	77960	26563	50340	43705
profit	0.3284	0.3575	0.7038	0.7777	0.7305	**2.1522**
lprod	211402	289121	215240	180152	340536	211705
TTL_EMP	43.766	46.422	39.663	34.681	42.783	28.372
GRSPAYRL	2E+06	2E+06	2E+06	1E+06	2E+06	1E+06
cost/employee	**886.99**	**1544.7**	**1965.6**	**765.93**	**1176.6**	**1540.4**

Table 90. State Means (Training variables)

Variable	Mean
gprofit	4.9384322
glprod	1.0671621
Totalcost	38656.26
profit	0.567772
lprod	183668.15
TTL_EMP	23.2108987
GRSPAYRL	893777.93
Tech1	0.1550972
Tech2	0.0351963
Tech3	0.0255731
NewProc	0.1937371
NewProd	0.2759772
FirstInn	0.0354046
totalcost_pe	7834.29
TechUse	0.1063493
CompUse	0.5094234
HRM1	0.159947
HRM2	0.0854579
HRM3	0.2186059
HRM4	0.120197
HRM5	0.1152816
HRM6	0.0473055
Educ	2.7241069
ClassTrain	0.208633
JobTrain	0.215433
HelpTrain	0.0255355
Cost/Employee	1665.43573
NoHelpTrain	0.0526488

Table 91. Mean values for the HRM, Training, ICT, Educ, COMP variables

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	4	-139.4476	6	1512.77	4-6
glprod	1	0.6564853	3	4.4286209	1-3
profit	7	0.1806262	15	2.1521788	7-15
lprod	1	149844.33	3	402844.51	1-3

Table 92. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (Training variables).

State # (bin)	000000	000001	000010	000011	000100	000101	000110	000111	001000	001001
State # (dec)	0	1	2	3	4	5	6	7	8	9
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	31.201	1.7587	**-1124.1**	-0.7856	17.888	-2.4542	5.814	6.2143	1.8745	26.809
glprod	1.0824	0.7679	1.1958	0.198	0.6319	1.9466	0.6436	0.2313	1.5449	1.1239
Totalcost	22903	29779	174235	4644.2	12350	32528	9448.8	71537	16523	7935.9
profit	0.5556	0.2599	0.4059	0.0984	0.8461	0.5584	0.4709	0.6626	0.4789	1.008
lprod	177337	172120	259814	197104	163805	256852	163720	220049	222390	196057
TTL_EMP	16.601	49.101	41.753	42.826	40.481	48.834	46.845	75.536	31.214	30.777
GRSPAYRL	606155	2E+06	2E+06	2E+06	1E+06	2E+06	2E+06	4E+06	1E+06	1E+06
cost/employee	**1379.6**	**606.5**	**4172.9**	**108.44**	**305.08**	**666.09**	**201.7**	**947.05**	**529.36**	**257.85**

State # (bin)	001010	001011	001100	001101	001110	001111	010000	010001	010010	010011
State # (dec)	10	11	12	13	14	15	16	17	18	19
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-26.183	2.3512	6.4779	1.8452	4.4649	0.1343	2.7013	-3.6492	-1.0219	-0.4562
glprod	0.3088	0.5619	0.3187	0.6215	1.9671	0.2266	1.3749	**7.6477**	2.9572	2.5798
Totalcost	111021	187829	29193	3E+06	71301	49075	17335	874480	14762	9568.2
profit	0.4121	0.2682	0.6609	0.375	0.7666	0.1167	0.7419	0.4542	0.1797	0.0261
lprod	172616	284092	178217	236834	230432	151289	261196	292977	**885066**	377559
TTL_EMP	37.963	54.461	37.104	50.299	60.43	50.338	32.165	56.945	33.563	6.5773
GRSPAYRL	2E+06	3E+06	2E+06	3E+06	3E+06	2E+06	2E+06	2E+06	1E+06	124509
cost/employee	**2924.5**	**3448.9**	**786.79**	**54970**	**1179.9**	**974.92**	**538.94**	**15357**	**439.82**	**1454.7**

State # (bin)	010100	010101	010110	010111	011000	011001	011010	011100	011110	011111
State # (dec)	20	21	22	23	24	25	26	28	30	31
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-1.7163	-1.0743	3.9204	2.7733	-3.2295	5.0979	1.0191	2.0604	7.1429	12.921
glprod	0.7459	-0.3632	0.3201	**-0.8232**	0.6787	0.1517	0.2262	0.2166	0.2536	-0.2656
Totalcost	48612	37595	99299	0	12914	31385	45571	126000	32846	24386
profit	0.062	0.0503	0.1985	0.6378	0.2098	0.0794	1.0127	0.2339	0.2673	1.7074
lprod	149458	135226	143399	96039	153608	148925	196751	146849	203555	171996
TTL_EMP	21.52	26.491	98.638	11.925	24.657	21.862	38.233	43.01	68.926	43.891
GRSPAYRL	501058	2E+06	4E+06	399259	943801	933195	2E+06	2E+06	3E+06	1E+06
cost/employee	**2258.9**	**1419.2**	**1006.7**	**0**	**523.72**	**1435.6**	**1191.9**	**2929.6**	**476.54**	**555.61**

State # (bin)	100000	100001	100010	100011	100100	100101	100110	100111	101000	101001
State # (dec)	32	33	34	35	36	37	38	39	40	41
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	13.191	1.2461	-0.5395	2.1849	2.6063	-0.2183	14.385	3.964	-5.5987	-16.216
glprod	1.0494	0.3163	0.5792	0.3333	2.7222	-0.708	1.6024	0.0267	0.7445	0.3048
Totalcost	27447	37975	59668	108202	7914.4	0	61095	8139.4	30539	20793
profit	0.461	0.3099	0.5365	0.7388	0.8806	0.1706	0.4756	0.27	0.3952	0.8718
lprod	190587	192985	160633	340668	322904	312975	356350	149491	175097	226874
TTL_EMP	33.741	57.742	52.35	93.278	36.396	75	66.544	36.241	35.107	38.716
GRSPAYRL	1E+06	2E+06	2E+06	4E+06	1E+06	4E+06	3E+06	1E+06	1E+06	2E+06
cost/employee	**813.45**	**657.68**	**1139.8**	**1160**	**217.46**	**0**	**918.12**	**224.59**	**869.88**	**537.06**

State # (bin)	101010	101011	101100	101101	101110	101111	110000	110001	110010	110011
State # (dec)	42	43	44	45	46	47	48	49	50	51
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	30.289	**427.86**	8.7748	0.5046	32.815	24.144	12.704	-0.9684	6.0818	179.73
glprod	0.7891	1.151	1.2921	0.5186	1.2525	1.0464	1.0058	1.3201	1.1176	6.2583
Totalcost	83082	5860.6	28770	17817	49538	218199	18354	0	18993	1E+06
profit	0.8104	0.447	1.0105	0.21	1.5632	0.7553	0.4503	0.0231	0.3867	**3.3409**
lprod	210962	201822	256879	138225	191145	177977	129871	**84774**	289455	634910
TTL_EMP	53.678	25.867	46.172	36.862	46.043	51.779	35.616	1	61.799	115.69
GRSPAYRL	2E+06	1E+06	2E+06	1E+06	2E+06	2E+06	1E+06	25000	2E+06	5E+06
cost/employee	**1547.8**	**226.56**	**623.1**	**483.35**	**1075.9**	**4214**	**515.33**	**0**	**307.33**	**9813.4**

State # (bin)	110100	110101	110110	110111	111000	111010	111011	111100	111101	111110
State # (dec)	52	53	54	55	56	58	59	60	61	62
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-0.5166	-1.5425	-2.4331	1.5018	14.715	-1.4764	5.3696	2.1857	-15.191	6.1131
glprod	1.0532	0.2929	1.4603	0.3007	0.7313	1.0765	1.2106	1.0671	0.5671	0.3835
Totalcost	14857	700.08	43165	56861	149047	195552	9947.5	32105	10831	29752
profit	0.0987	**-0.0749**	0.2549	0.2857	0.5648	0.3668	0.2524	1.1129	0.7859	0.7495
lprod	145997	90634	282020	144776	167543	176141	175024	193591	146532	159276
TTL_EMP	22.878	13.726	32.702	39.445	33.884	36.267	39.668	30.806	24.415	52.906
GRSPAYRL	907384	582648	988090	2E+06	1E+06	1E+06	2E+06	1E+06	887339	2E+06
cost/employee	**649.4**	**51.003**	**1320**	**1441.5**	**4398.7**	**5392.1**	**250.77**	**1042.2**	**443.62**	**562.35**

State # (bin)	111111
State # (dec)	63
Variable	**Mean**
gprofit	3.2533
glprod	2.8249
Totalcost	23011
profit	0.3362
lprod	171452
TTL_EMP	29.257
GRSPAYRL	1E+06
cost/employee	**786.5**

Table 93. State Means (Human Resource Management variables)

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	2	-1124.05	43	427.86306	2-3-11-43
glprod	23	-0.823241	17	7.6476929	23-19-17
profit	53	-0.074922	51	3.340858	53-55-51
lprod	49	84774	18	885066.44	49-55-51-18

Table 94. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (Human Resource Management variables).

State # (bin)	000000	000001	000010	000100	000101	000110	001000	001001	001010	001011
State # (dec)	0	1	2	4	5	6	8	9	10	11
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	7.3918	6.4107	-0.0649	1.7279	-1.7851	75.415	210.23	4.9141	3.4373	-2.1027
glprod	0.6164	-0.1599	0.4662	0.7771	0.3069	0.2005	0.8941	0.3977	-0.2737	-0.0646
Totalcost	29543	9498.9	8174.1	14198	3975.8	58493	16044	11029	7630.5	1392.5
profit	0.4735	0.4381	0.2008	0.3545	0.3444	0.1821	0.336	0.4188	0.1926	0.1739
lprod	146092	95964	163589	129864	83894	102979	150123	144820	97805	150267
TTL_EMP	15.51	16.724	25.719	23.433	17.746	31.927	30.189	27.475	16.033	20.65
GRSPAYRL	464284	430035	875805	636497	406024	1E+06	1E+06	937512	602964	788868
totalcost_pe	13838	702.32	131.82	547.4	317.31	545.3	500.3	297.97	207.43	508.52
cost/employee	**1904.8**	**567.98**	**317.82**	**605.91**	**224.04**	**1832.1**	**531.43**	**401.41**	**475.91**	**67.436**

State # (bin)	001100	001101	001110	010000	010001	010010	010100	010101	010110	011000
State # (dec)	12	13	14	16	17	18	20	21	22	24
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	128.27	-10.533	-1.3728	2.3987	4.1709	1.1387	11.54	32.79	-34.813	1.7569
glprod	0.3855	0.6242	-0.1311	0.7678	1.0106	0.252	0.1154	0.0636	0.2989	0.5906
Totalcost	38560	4668.5	3436.6	21692	8614.6	7873.8	40350	228521	7811.7	63403
profit	0.3204	0.2894	0.2347	0.4729	1.5853	0.1141	0.3966	0.2398	2.5798	0.3655
lprod	124968	125894	103213	141212	137139	144910	115236	154291	323249	157428
TTL_EMP	33.114	19.059	19.63	29.877	19.064	14.853	35.436	22.264	31.489	49.242
GRSPAYRL	1E+06	728353	680207	927339	547041	420881	1E+06	574090	1E+06	2E+06
totalcost_pe	1117.4	135.78	64.922	442.44	601.16	237.22	1340.5	10360	146.05	720.96
cost/employee	**1164.5**	**244.95**	**175.07**	**726.03**	**451.88**	**530.12**	**1138.7**	**10264**	**248.08**	**1287.6**

State # (bin)	011001	011010	011100	011101	011110	100000	100001	100010	100011	100100
State # (dec)	25	26	28	29	30	32	33	34	35	36
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	-1.9668	-0.481	1.207	-0.2327	-0.3364	7.8645	3.2558	5.1233	4.9722	**-250.46**
glprod	-0.3898	1.1894	1.4084	0.693	**-0.805**	1.3577	0.7977	0.8016	5.5583	1.434
Totalcost	11994	1099.9	14779	350162	54508	44235	8679.8	17395	3919.2	75525
profit	**-0.1131**	0.08	0.3406	0.255	0.3421	0.6961	0.5669	0.4547	0.4776	0.5934
lprod	110702	155703	140072	240000	**48744**	213696	182385	165948	471490	227719
TTL_EMP	28.294	77.63	28.685	103.1	27.814	19.88	22.219	28.378	18.961	26.342
GRSPAYRL	1E+06	3E+06	1E+06	3E+06	571192	826778	960310	1E+06	897114	1E+06
totalcost_pe	67.124	46.371	1101.6	1902.3	2884.7	7193.4	444.04	1219	114.95	10895
cost/employee	**423.91**	**14.169**	**515.23**	**3396.4**	**1959.7**	**2225.2**	**390.64**	**612.96**	**206.7**	**2867.1**

State # (bin)	100101	100110	100111	101000	101001	101010	101011	101100	101101	101110
State # (dec)	37	38	39	40	41	42	43	44	45	46
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	5.2633	0.8501	-0.8993	29.503	3.1333	4.6847	29.067	4.9385	5.4315	5.9532
glprod	1.0168	1.2052	1.2478	1.8604	1.0571	1.4401	**9.1541**	2.0242	0.6314	2.2379
Totalcost	12539	44053	11369	41855	19701	49942	189363	93465	22928	48467
profit	0.4739	0.8465	0.1974	0.7054	0.2904	0.3814	0.4178	0.6868	0.944	0.5247
lprod	255669	242972	364023	249505	188007	232472	**659628**	243601	194560	378144
TTL_EMP	25.199	33.248	13.287	37.121	23.626	49.509	95.672	40.882	35.678	45.64
GRSPAYRL	1E+06	2E+06	588390	2E+06	1E+06	3E+06	6E+06	2E+06	2E+06	3E+06
totalcost_pe	388.79	464.78	106.51	844.75	4078.7	1020.8	424.24	7097.3	567.52	902.88
cost/employee	**497.59**	**1325**	**855.64**	**1127.5**	**833.85**	**1008.7**	**1979.3**	**2286.2**	**642.63**	**1061.9**

State # (bin)	101111	110000	110001	110010	110100	110101	110110	111000	111001	111010
State # (dec)	47	48	49	50	52	53	54	56	57	58
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	0.2129	0.6375	-76.328	-4.5631	19.095	4.6959	**7852.8**	36.142	0.5079	-2.5678
glprod	0.5793	0.9348	1.8885	1.595	1.8471	1.7566	3.9996	2.2484	1.0219	2.9941
Totalcost	60281	35310	10575	37559	32342	14562	8100.1	45884	16222	37778
profit	0.2046	0.4132	0.7323	0.2185	0.9284	1.4142	**2.6963**	0.8884	0.1963	0.2886
lprod	118324	188658	155985	284169	193357	281393	243304	245547	148778	422037
TTL_EMP	40.191	25.95	19.55	35.832	30.565	37.943	16.005	38.563	23.389	76.189
GRSPAYRL	2E+06	960377	675531	2E+06	1E+06	1E+06	768892	2E+06	793262	4E+06
totalcost_pe	451.53	1071.7	302.12	199.99	610.84	995.35	321.14	3091.6	1264.9	1407.4
cost/employee	**1499.9**	**1360.7**	**540.9**	**1048.2**	**1058.2**	**383.78**	**506.1**	**1189.8**	**693.6**	**495.85**

State # (bin)	111100	111101	111110
State # (dec)	60	61	62
Variable	**Mean**	**Mean**	**Mean**
gprofit	8.8439	34.97	5.2685
glprod	1.1767	1.4325	3.9505
Totalcost	77291	87091	107398
profit	1.5275	0.7526	2.3205
lprod	215728	201366	473029
TTL_EMP	47.699	65.171	56.609
GRSPAYRL	2E+06	3E+06	3E+06
totalcost_pe	5130.2	980.89	1759.1
cost/employee	**1620.4**	**1336.3**	**1897.2**

Table 95. State Means (Computer Use and Training)

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	36	-250.4572	54	7852.77	36-52-54
glprod	30	-0.804981	43	9.1540786	30-14-10-11-43
profit	25	-0.113125	54	2.6963176	25-17-16-18-22-54
lprod	30	48743.7	43	659627.51	30-14-10-11-43

Table 96. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (Computer Use and Training).

State # (bin)	000000	000001	000010	000011	000100	000101	000110	000111	001000	001001
State # (dec)	0	1	2	3	4	5	6	7	8	9
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-19.411	15.968	0.4967	4.7449	**377.31**	0.1081	10.142	-0.9188	1.0988	1.2407
glprod	0.9421	0.8081	1.0826	5.6106	0.8768	0.8732	0.8687	1.0036	0.9913	4.351
Totalcost	0	0	0	0	0	0	0	0	181035	518791
profit	0.4896	0.3558	0.5651	1.7115	0.6494	0.2089	0.7485	0.4382	0.2039	0.1948
lprod	175201	134446	186817	349163	195535	240194	182383	170960	144176	422180
TTL_EMP	16.227	39.15	19.627	35.552	33.391	52.177	38.001	62.083	25.717	233.77
GRSPAYRL	598285	2E+06	668154	1E+06	1E+06	3E+06	1E+06	3E+06	1E+06	1E+07
cost/employee	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**7039.6**	**2219.3**

State # (bin)	001010	001011	001100	001101	001110	001111	010000	010001	010010	010011
State # (dec)	10	11	12	13	14	15	16	17	18	19
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	0.0186	-0.1153	-0.3724	-0.5403	8.3381	1.7988	-3.8844	9.6806	-1.736	-1.2532
glprod	1.405	**16.657**	1.2843	1.2535	1.8607	1.1166	1.0128	2.3498	-0.021	5.8401
Totalcost	66031	268890	165446	3E+06	133915	325785	66967	170837	53367	27444
profit	0.3592	0.0151	0.4503	0.5685	1.5145	0.6638	0.6731	1.5764	0.345	0.1681
lprod	188766	514135	177109	154174	187019	342055	149047	381844	112654	345220
TTL_EMP	26.258	28.792	35.313	133.19	35.934	142.76	32.183	81.914	24.967	29.097
GRSPAYRL	854216	1E+06	1E+06	6E+06	1E+06	5E+06	1E+06	2E+06	924444	1E+06
cost/employee	**2514.7**	**9339.1**	**4685.1**	**23045**	**3726.7**	**2282.1**	**2080.8**	**2085.6**	**2137.5**	**943.18**

State # (bin)	010100	010101	010110	010111	011000	011001	011010	011100	011110	011111
State # (dec)	20	21	22	23	24	25	26	28	30	31
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-1.0918	-3.1813	2.7479	1.4937	8.9812	-1.5372	-0.3488	-0.7501	0.4287	-0.8525
glprod	0.6689	2.0499	1.2293	0.8362	1.0366	1.4972	1.6624	0.3616	3.0265	4.3702
Totalcost	191664	2E+06	82875	89241	203030	585099	351769	5E+06	473462	2E+06
profit	0.2351	0.2716	0.5933	0.6442	0.4674	0.3374	0.1715	0.6287	0.1924	0.1601
lprod	136901	357231	217031	199792	220466	194025	189643	201130	188842	439657
TTL_EMP	51.859	199.94	57.097	67.037	41.889	289.39	109.78	408.87	65.257	434.73
GRSPAYRL	2E+06	1E+07	2E+06	3E+06	2E+06	1E+07	3E+06	2E+07	4E+06	2E+07
cost/employee	**3695.9**	**10936**	**1451.5**	**1331.2**	**4846.8**	**2021.8**	**3204.3**	**11408**	**7255.3**	**3656**

State # (bin)	100000	100001	100010	100011	100100	100101	100110	100111	101000	101001
State # (dec)	32	33	34	35	36	37	38	39	40	41
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	11.162	0.1319	11.569	-8.4807	23.576	-20.125	4.898	13.113	**-52.964**	9.5635
glprod	1.0548	1.5399	1.4451	7.9346	2.721	2.2775	1.1884	0.6588	0.6221	0.0553
Totalcost	65169	23714	33246	102080	714442	471053	83801	1E+06	181942	3E+06
profit	0.8028	0.3399	0.6473	0.4547	0.4902	**1.9873**	0.6279	1.8063	0.4083	0.5337
lprod	204767	147246	192827	583383	224412	256326	199278	243938	154750	177933
TTL_EMP	25.534	42.028	22.584	98.028	31.977	47.303	37.784	70.134	30.222	166.04
GRSPAYRL	1E+06	2E+06	734956	5E+06	1E+06	2E+06	2E+06	3E+06	2E+06	8E+06
cost/employee	**2552.3**	**564.24**	**1472.1**	**1041.3**	**22343**	**9958.1**	**2217.9**	**15515**	**6020.1**	**16347**

State # (bin)	101010	101011	101100	101101	101110	101111	110000	110001	110010	110011
State # (dec)	42	43	44	45	46	47	48	49	50	51
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	4.1139	-1.4851	1.2582	4.7688	3.6742	-0.1209	5.7901	-1.1097	0.7643	7.5267
glprod	0.0193	0.5941	0.8025	8.2611	1.0492	0.3803	0.511	**-0.1353**	7.3026	1.3102
Totalcost	128766	232719	534868	1E+06	681743	284870	130805	162214	115711	173630
profit	0.3896	0.0966	0.6777	0.1091	0.3388	0.091	0.2353	0.0129	0.3216	0.8921
lprod	110842	200263	189962	**809384**	198369	286917	168649	**66153**	278249	270808
TTL_EMP	51.389	89.588	59.627	76.085	88.282	79.218	39.237	78.983	35.655	49.879
GRSPAYRL	2E+06	4E+06	3E+06	5E+06	3E+06	5E+06	2E+06	2E+06	1E+06	2E+06
cost/employee	**2505.7**	**2597.6**	**8970.2**	**14447**	**7722.4**	**3596**	**3333.7**	**2053.8**	**3245.3**	**3481**

State # (bin)	110100	110101	110110	110111	111000	111010	111011	111100	111101	111110
State # (dec)	52	53	54	55	56	58	59	60	61	62
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	-2.2142	-4.4469	23.076	1.478	9.7339	-6.1381	-13.854	-3.5306	19.391	8.3832
glprod	2.0745	0.5153	0.4646	1.8665	2.1794	3.3866	1.0863	0.6057	1.9635	0.7259
Totalcost	166759	844116	647566	458388	2E+06	3E+06	3E+06	1E+06	892292	865681
profit	0.1552	0.3006	0.9455	0.1092	0.3258	0.3093	**-0.0018**	0.4418	1.282	0.6033
lprod	213014	226198	160422	234818	340966	194298	212792	247053	134711	223607
TTL_EMP	33.997	96.413	56.238	168.97	179.18	57.371	710.64	151.99	90.19	178.84
GRSPAYRL	1E+06	5E+06	2E+06	7E+06	8E+06	1E+06	3E+07	9E+06	4E+06	8E+06
cost/employee	**4905.1**	**8755.2**	**11515**	**2712.9**	**10296**	**58765**	**3853.4**	**6862.3**	**9893.5**	**4840.6**

State # (bin)	111111
State # (dec)	63
Variable	**Mean**
gprofit	-0.2857
glprod	0.9264
Totalcost	2E+06
profit	0.1643
lprod	354286
TTL_EMP	573.39
GRSPAYRL	4E+07
cost/employee	**3307.8**

Table 97. State Means (ICT and Innovation)

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	40	-52.96409	4	377.30883	40-32-0-4
glprod	49	-0.13527	11	16.656736	49-17-19
profit	59	-0.001751	37	1.9872589	59-43-35-3
lprod	49	66152.58	45	809384.06	49-33-1-9

Table 98. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (ICT and Innovation).

State # (bin)	00000000	00000001	00000010	00000100	00000101	00000110	00001000	00001001
State # (dec)	0	1	2	4	5	6	8	9
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	4.38226	12.3997	2.10473	3.5964	-0.31383	**7708.23**	52.3176	0.20708
glprod	0.74299	0.07629	0.65549	0.67484	-0.15084	1.6787	1.30891	0.11977
Totalcost	44259.1	10747.2	4559.64	15568.7	3004.2	4684.1	15870.2	20449.7
profit	0.46923	0.41652	0.44247	0.42951	0.10662	0.90396	0.35028	0.12501
lprod	155465	104077	208704	142286	150191	221501	178474	116661
TTL_EMP	14.5317	20.3363	24.9372	22.7419	18.1163	25.3374	27.7995	36.5275
GRSPAYRL	430606	696916	1007608	593406	523329	1051360	944006	1033322
totalcost_pe	20543.1	1338.83	702.064	771.862	177.203	318.639	493.33	240.722
cost/employee	**3045.7**	**528.473**	**182.845**	**684.585**	**165.828**	**184.869**	**570.883**	**559.844**

State # (bin)	00001010	00001100	00001101	00001110	00010000	00010001	00010100	00011000
State # (dec)	10	12	13	14	16	17	20	24
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	8.57212	-0.49065	3.97693	-0.70185	8.3548	-0.96644	0.76628	-0.7579
glprod	0.26073	1.20702	0.53445	0.70922	0.75912	-0.0975	-0.1089	0.34703
Totalcost	14388.8	63656.6	8022.62	22539.9	14779.2	2618.53	17540.6	99884.1
profit	0.45532	0.67523	0.7675	0.17302	0.28285	0.06122	0.50057	0.05011
lprod	169068	184860	144188	157072	126868	139548	68818.1	98539.7
TTL_EMP	28.5464	33.5776	15.1375	31.5774	19.7437	15.1484	27.6618	37.0056
GRSPAYRL	1231909	1194738	546153	1100709	567435	379795	618913	1119523
totalcost_pe	405.779	5881.53	133.939	603.7	197.819	10.1802	259.377	30184.2
cost/employee	**504.047**	**1895.8**	**529.982**	**713.799**	**748.552**	**172.859**	**634.11**	**2699.16**

State # (bin)	00011100	00100000	00100001	00100010	00100100	00100101	00100110	00101000
State # (dec)	28	32	33	34	36	37	38	40
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-2.14531	-2.21721	3.24426	-0.93602	1.09578	-5.90011	-0.82006	-0.89528
glprod	0.60766	0.32981	0.4527	0.29728	0.38085	-0.32046	0.29775	1.66282
Totalcost	26029.3	10797.2	27458.7	2935.9	14227	3373.53	17281.9	38644.9
profit	0.0473	0.48702	0.8252	0.0651	0.47214	0.66256	0.34696	0.20238
lprod	221820	131877	121109	84521.9	140155	**63579.6**	96350.9	195457
TTL_EMP	45.4893	19.7279	18.9276	21.6619	22.4171	23.6976	14.9042	28.3238
GRSPAYRL	1864826	536866	622212	570112	619640	403428	485214	923299
totalcost_pe	909.383	265.124	181.115	31.3726	442.716	50.2095	239.669	1246.78
cost/employee	**572.206**	**547.306**	**1450.72**	**135.533**	**634.651**	**142.358**	**1159.53**	**1364.4**

State # (bin)	00101001	00101010	00101100	00101101	00101110	00110000	00110001	00110010
State # (dec)	41	42	44	45	46	48	49	50
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-0.49516	0.9025	371.599	-1.28713	-1.49702	9.06909	-56.0542	3.1657
glprod	0.56003	2.96554	0.28848	-0.26896	0.99323	1.14074	1.275	0.6031
Totalcost	4234.24	62481.9	17839.8	39554.6	60436.2	28976.7	7745.89	13805.3
profit	**-0.05555**	0.51983	0.6618	0.97151	0.86371	0.66483	0.71336	0.49546
lprod	152954	175684	140487	162262	161681	192120	161567	171492
TTL_EMP	16.6194	42.0637	36.5032	25.2411	67.2924	19.9294	21.0052	26.63
GRSPAYRL	428132	1383878	1155681	764548	3161181	704546	702924	978706
totalcost_pe	145.822	869.323	225.492	224.882	620.456	4032.91	344.004	1156.28
cost/employee	**254.777**	**1485.41**	**488.72**	**1567.07**	**898.114**	**1453.97**	**368.761**	**518.41**

State # (bin)	00110100	00110101	00110110	00111000	00111001	00111010	00111011	00111100
State # (dec)	52	53	54	56	57	58	59	60
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	3.19279	17.9957	4.46203	217.297	2.71104	2.98179	-0.24337	7.38433
glprod	1.59861	1.15391	1.32107	1.80052	0.71223	0.47485	0.55127	1.34908
Totalcost	86571.4	54505.5	36543.1	39384.1	7345.41	31169.6	38683.2	43005.2
profit	0.59667	0.58782	1.29843	0.75911	0.40349	0.41934	0.47292	0.67936
lprod	218030	184853	213386	227993	182014	145784	134462	196689
TTL_EMP	25.3504	22.3174	26.6452	39.0329	24.4612	28.8376	50.6315	34.2132
GRSPAYRL	928455	710997	1153183	1558565	920571	1255305	1880902	1373322
totalcost_pe	14580.8	2334.35	312.045	818.867	207.921	1247.16	120.545	2000.1
cost/employee	**3415**	**2442.29**	**1371.47**	**1009**	**300.288**	**1080.87**	**764.015**	**1256.98**

State # (bin)	00111101	00111110	00111111	01000000	01000001	01000010	01000100	01000101
State # (dec)	61	62	63	64	65	66	68	69
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	1.16243	2.90498	331.239	1.06417	56.9797	1.93535	6.48106	0.70684
glprod	0.72693	3.01396	1.85059	0.74771	0.8123	0.22537	1.13895	-0.24355
Totalcost	35857.3	36384.6	26492.4	11483.5	2105.71	9505.07	49232.8	4765.62
profit	0.6651	0.53769	**5.57541**	0.54784	0.94178	0.22471	0.57535	0.48258
lprod	190665	386105	424541	173376	136005	131315	186149	109113
TTL_EMP	32.8669	31.3656	10.4882	15.8208	13.0927	34.5601	27.0193	29.5203
GRSPAYRL	1448750	1329524	398251	635190	411654	1437103	1079602	830310
totalcost_pe	974.977	1289.33	374.742	541.187	177.298	124.896	2545.64	18.9481
cost/employee	**1090.99**	**1160.02**	**2525.92**	**725.844**	**160.83**	**275.031**	**1822.13**	**161.435**

State # (bin)	01000110	01001000	01001001	01001010	01001100	01001101	01001110	01010000
State # (dec)	70	72	73	74	76	77	78	80
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	79.322	29.874	8.59332	17.6722	2.96044	32.8682	21.5005	41.3139
glprod	5.61205	2.00195	1.27841	2.92138	3.35533	1.61018	2.96281	0.78375
Totalcost	169766	34498.2	34305.1	20744.3	40327.1	8292.97	7578.33	17513.8
profit	5.04721	1.30898	0.31132	0.53957	1.17734	0.66615	1.6829	0.39933
lprod	696247	244104	281092	361044	315765	208582	**938500**	164947
TTL_EMP	82.854	36.6724	26.6813	35.5379	35.2957	33.9006	29.5542	19.8084
GRSPAYRL	4131461	1666282	1168383	1627403	1665882	1662120	1368555	827949
totalcost_pe	1796.38	714.962	2069.42	638.451	680.097	476.929	233.996	1267.27
cost/employee	**2048.97**	**940.712**	**1285.74**	**583.725**	**1142.55**	**244.626**	**256.422**	**884.159**

State # (bin)	01010001	01010010	01010100	01010101	01010110	01011000	01011001	01011010
State # (dec)	81	82	84	85	86	88	89	90
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	2.15177	0.57692	12.5283	-35.9703	-4.40578	4.16699	1.74887	11.9705
glprod	0.15626	0.92404	0.77698	0.85452	3.29558	1.14086	0.16196	0.72
Totalcost	2055.53	48283	44919.4	18185.9	11635.9	25665.8	53446.1	29104.3
profit	0.47111	0.2589	0.55252	0.82586	0.24583	0.40728	0.15385	0.21348
lprod	122840	189252	181462	236982	153149	204826	116675	183518
TTL_EMP	22.2878	35.1167	30.8491	28.4179	19.4863	28.0463	14.1761	30.5791
GRSPAYRL	913781	1549378	1353114	1660237	917629	1246272	667271	1653162
totalcost_pe	63.7568	243.349	1698.97	337.134	685.427	813.176	15815.5	514.229
cost/employee	**92.2266**	**1374.93**	**1456.1**	**639.944**	**597.133**	**915.122**	**3770.15**	**951.771**

State # (bin)	01011100	01011101	01011110	01100000	01100001	01100010	01100100	01100101
State # (dec)	92	93	94	96	97	98	100	101
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-5.84507	-0.12028	0.92569	5.39179	3.44898	-0.26744	**-1197.47**	6.0215
glprod	2.43933	0.6931	0.68665	1.17104	0.29894	1.64429	1.30509	1.26982
Totalcost	35562.2	47874.9	284320	45374	7070.64	15333.5	27113.6	12541.9
profit	0.3862	0.33812	0.25351	0.70147	0.47645	0.1931	0.40879	0.81519
lprod	253343	139353	185596	195688	127432	258664	193601	211784
TTL_EMP	33.8458	32.2167	69.5904	22.2774	19.03	25.2689	29.7253	22.7408
GRSPAYRL	1663103	1531918	4123839	952053	733413	1256560	1372216	717330
totalcost_pe	1320.18	341.665	6430.06	4520.16	378.74	631.792	1053.03	1341.66
cost/employee	**1050.71**	**1486.03**	**4085.63**	**2036.77**	**371.551**	**606.815**	**912.139**	**551.515**

State # (bin)	01100110	01101000	01101001	01101010	01101100	01101101	01101110	01110000
State # (dec)	102	104	105	106	108	109	110	112
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	4.34718	-25.4174	5.63772	-0.66459	7.99798	-8.66034	2.13683	4.51358
glprod	0.55908	1.21244	0.36625	2.37538	1.31325	0.8346	0.22901	1.91691
Totalcost	13548.7	51047	7258.73	72506	79823.3	9391.28	34555.5	39036
profit	0.51302	0.69446	0.4166	0.18994	0.70736	0.37411	0.30323	0.68374
lprod	127645	226157	149490	285041	182711	167144	135885	242700
TTL_EMP	27.2207	37.34	21.2272	66.5961	43.8982	22.3659	53.9379	29.5091
GRSPAYRL	1350391	1739632	788141	3262189	2065234	936418	3050203	1536333
totalcost_pe	441.847	735.624	447.711	1341.83	828.883	252.975	682.785	806.296
cost/employee	**497.735**	**1367.09**	**341.954**	**1088.74**	**1818.37**	**419.893**	**640.653**	**1322.85**

State # (bin)	01110001	01110010	01110100	01110101	01110110	01111000	01111001	01111010
State # (dec)	113	114	116	117	118	120	121	122
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	8.05168	12.5218	21.9759	4.73796	39.1303	-12.8664	2.76503	0.43179
glprod	0.83097	0.59191	2.13243	2.65797	1.25192	2.5688	0.59743	1.09443
Totalcost	14109.6	32877.4	59560.2	15526.5	125805	45016.4	14248.4	39461.8
profit	0.38027	0.48019	0.86364	0.46439	2.43097	0.80369	0.33333	0.26217
lprod	227132	124614	236455	550310	341996	286724	167403	276996
TTL_EMP	25.5184	35.5237	38.1112	37.1591	46.6626	52.4498	46.6819	48.3019
GRSPAYRL	1170887	1684335	2062425	2027898	2754001	2798568	2348066	2747695
totalcost_pe	856.022	1647.64	1478.63	111.398	434.916	628.146	1701.7	526.331
cost/employee	**552.917**	**925.506**	**1562.8**	**417.838**	**2696.06**	**858.276**	**305.224**	**816.981**

State # (bin)	01111100	01111101	01111110	01111111	10000000	10000001	10000010	10000100
State # (dec)	124	125	126	127	128	129	130	132
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	1.49587	22.7317	8.33401	0.58769	-8.01612	-0.46995	-0.66127	-1.13383
glprod	1.95998	0.33442	2.29872	1.1618	0.70887	0.79088	1.01896	2.74343
Totalcost	207380	18663.4	51439.6	10026	22821.3	10705.5	4204.73	90636.2
profit	0.52483	2.23759	1.39935	0.11681	0.52823	1.0045	0.18608	1.41916
lprod	252565	233228	347110	122148	211151	333478	158223	323963
TTL_EMP	65.1174	56.6797	42.2957	38.3396	21.6229	19.0249	21.1312	34.8378
GRSPAYRL	3601574	2512518	2483613	2206218	1230592	871920	1050208	2038143
totalcost_pe	21772.2	616.569	652.496	72.0729	697.847	524.423	109.56	751.059
cost/employee	**3184.71**	**329.278**	**1216.19**	**261.506**	**1055.42**	**562.711**	**198.982**	**2601.66**

State # (bin)	10000101	10000110	10001000	10001001	10001010	10001100	10001101	10001110
State # (dec)	133	134	136	137	138	140	141	142
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-7.67413	1.52636	4.97859	-1.12321	2.47129	6.12775	3.02526	-1.56023
glprod	0.62391	-0.4822	1.33076	**6.66036**	0.87787	3.56061	2.38046	3.82108
Totalcost	21342.1	5973.77	39131.4	4480.64	23397.5	42045.7	80545.8	17274.5
profit	0.48788	0.57901	0.4263	0.09085	0.21536	1.26812	0.18526	0.69068
lprod	346033	272790	223567	270066	136485	365000	212188	411783
TTL_EMP	42.4945	31.2995	38.254	41.4005	53.9206	46.3726	97.2876	44.3739
GRSPAYRL	1907509	1785774	2101051	2169975	2706630	2556233	2976472	2404413
totalcost_pe	786.084	47.9908	733.34	511.312	80.3555	597.729	230.765	195.688
cost/employee	**502.232**	**190.858**	**1022.94**	**108.227**	**433.926**	**906.691**	**827.914**	**389.294**

State # (bin)	10010000	10010001	10010010	10010100	10010101	10011000	10011001	10011010
State # (dec)	144	145	146	148	149	152	153	154
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	96.1104	1.88742	2.3708	-21.1382	5.38989	22.5984	-0.34245	1.62258
glprod	1.41046	0.60525	1.05591	0.66301	**-0.50319**	1.4686	-0.28112	2.07209
Totalcost	80570.5	33091	42608	22326.4	2973.76	28362.8	16725.8	256190
profit	0.58606	0.31555	0.03543	0.28394	0.12785	0.28915	0.12169	0.30796
lprod	225835	112154	139722	229360	85076.4	209487	146859	317403
TTL_EMP	31.23	50.2805	25.6324	33.0388	26.9582	41.9975	39.3454	263.515
GRSPAYRL	1553847	2441111	1217670	1881059	1091944	2139473	1934326	1.7E+07
totalcost_pe	4543.27	1840.68	387.49	1299.51	11.9921	861.1	290.046	634.207
cost/employee	**2579.91**	**658.129**	**1662.27**	**675.761**	**110.31**	**675.344**	**425.103**	**972.203**

State # (bin)	10011100	10011101	10011110
State # (dec)	156	157	158
Variable	**Mean**	**Mean**	**Mean**
gprofit	0.39647	1.64006	-1.87491
glprod	1.72912	-0.01515	4.17776
Totalcost	799934	78449.2	255183
profit	0.84182	0.0394	0.02656
lprod	244626	127961	505967
TTL_EMP	59.6012	104.598	73.7122
GRSPAYRL	3577531	6212213	6126586
totalcost_pe	98407.8	541.196	1307.11
cost/employee	**13421.4**	**750.007**	**3461.89**

Table 99. State Means (Education and Training)

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	100	-1197.47	6	7708.23	100-9-1-0-2-6
glprod	149	-0.503187	137	6.660355	149-133-129-137
profit	41	-0.055546	63	5.5754102	41-57-59-63
lprod	37	63579.61	78	938499.98	37-5-13-77-76-78

Table 100. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (Education and Training).

State # (bin)	00000000	00000001	00000010	00000011	00000100	00000101	00000110	00000111
State # (dec)	0	1	2	3	4	5	6	7
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	33.71971	0.997733	8.637037	-0.90042	28.68448	-4.40996	1.843947	0.930677
glprod	0.663209	0.738054	0.411987	0.118766	0.501189	3.615598	2.217237	-0.18528
Totalcost	20880.73	10588.62	398479.6	7541.81	12289.98	19076.87	13121.2	9204.39
profit	0.459977	0.147684	0.223132	0.278147	1.298847	0.5248	0.231913	0.451932
lprod	141440.1	163634.2	155927.4	120014	188094	339458.6	253561.4	206469.9
TTL_EMP	13.80135	37.24312	34.28368	56.88121	42.47834	23.48082	47.12908	43.55875
GRSPAYRL	398410.4	1274879	1186891	2389152	1267943	982576.8	1778739	1829930
totalcost_pe	7659.96	315.3548	380330.5	996.3272	565.4483	261.0472	73.50335	23.59809
cost/employee	**1512.949**	**284.3108**	**11623.01**	**132.5888**	**289.3235**	**812.445**	**278.4098**	**211.3098**

State # (bin)	00001000	00001001	00001010	00001011	00001100	00001101	00001110	00001111
State # (dec)	8	9	10	11	12	13	14	15
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	0.342157	8.020373	-54.2015	0.371679	1.318274	3.500567	1.723067	0.275868
glprod	1.078931	0.422347	0.157402	0.253385	-0.02136	0.065074	0.29788	-0.33961
Totalcost	6574.54	2068.88	43561.8	154127.3	13598.95	17413.45	35850.6	23346.77
profit	0.333901	0.662921	0.358526	0.236282	0.465136	0.340878	0.294796	0.121115
lprod	174671.8	162744.2	128003.2	148877.5	120557.1	158427	152652	89214.89
TTL_EMP	21.55509	19.41714	32.27861	35.53746	25.58472	23.16137	39.31417	25.02426
GRSPAYRL	668293.1	612128.6	1141267	1759685	996089.4	748469.5	1662789	952424.6
totalcost_pe	318.514	293.6314	354.411	637.839	188.7875	415.5035	1091.05	281.0392
cost/employee	**305.0111**	**106.5491**	**1349.556**	**4337.037**	**531.5262**	**751.8315**	**911.9002**	**932.9653**

State # (bin)	00010000	00010010	00010100	00010110	00011000	00011001	00011010	00011011
State # (dec)	16	18	20	22	24	25	26	27
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	2.439546	-0.39761	-0.19989	1.885536	-12.6101	-3.56269	0.22103	-11.1498
glprod	0.028914	1.539108	1.847751	0.097488	0.260785	0.197057	0.043494	0.387591
Totalcost	14583.23	9776.98	8346.68	35562.07	8311.33	30637.31	25647.71	12820.78
profit	0.52418	0.363086	0.088363	0.241435	0.2523	**-0.22448**	0.517951	0.502202
lprod	134960.3	292155	163481.5	137666.3	104344.3	161004.8	150229.3	189891.3
TTL_EMP	22.31339	44.47249	23.32116	81.58788	19.41233	24.17061	29.16265	76.32495
GRSPAYRL	726232.7	1534752	656499.5	3344697	643317.6	1054861	876834	3301003
totalcost_pe	501.5448	111.7165	86.3732	55.66266	313.0199	417.7798	135.2536	284.3455
cost/employee	**653.564**	**219.8433**	**357.9016**	**435.8744**	**428.1469**	**1267.544**	**879.4711**	**167.9763**

State # (bin)	00011100	00011101	00011110	00011111	00100000	00100001	00100010	00100100
State # (dec)	28	29	30	31	32	33	34	36
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	2.005459	-0.23315	8.709961	-0.00933	-2.10161	1.219579	-1.63545	1.998155
glprod	-0.29155	0.256113	0.127128	-0.44951	0.317664	-0.00768	0.373998	1.504792
Totalcost	29154.62	26356.64	13160.93	18241.1	17987.67	3806.44	27924.33	5669.38
profit	0.124227	-0.08426	0.207239	0.462786	0.260907	0.474907	0.528098	0.536829
lprod	106140.8	173765.6	118573.6	105652.5	137832.4	133463.2	134929.5	281993.7
TTL_EMP	18.4216	28.19906	33.14177	40.29141	24.2489	25.03504	37.77721	33.93236
GRSPAYRL	554080.8	1182037	1185295	1263729	672675	823424.4	1176052	1066093
totalcost_pe	1007.35	332.2263	88.52624	644.4454	430.8866	268.3346	397.4608	140.7611
cost/employee	**1582.632**	**934.6636**	**397.1101**	**452.7292**	**741.7932**	**152.0445**	**739.1845**	**167.0788**

State # (bin)	00100110	00100111	00101000	00101001	00101010	00101011	00101100	00101101
State # (dec)	38	39	40	41	42	43	44	45
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	7.351705	0.402411	-1.2355	0.509642	12.38504	-3.62632	10.48369	1.745724
glprod	2.202055	-0.12694	0.498016	0.374436	0.322296	1.869077	0.808753	-0.24463
Totalcost	70699.59	3587.7	17953.28	20958.78	59184.97	3785.41	17904.76	21650.87
profit	0.582241	0.208791	0.347403	0.715339	0.3526	-0.00975	0.855926	0.194285
lprod	151579.7	139785.1	133548.2	201399.2	185652.8	172334.1	156553.1	100666.6
TTL_EMP	64.92493	21.44748	24.88087	18.86896	47.00222	30.39946	33.9031	24.23101
GRSPAYRL	2264519	839280.4	751297.8	679924.4	1675434	1197563	1125306	650905.8
totalcost_pe	2074.47	7.146082	440.1552	885.6865	2100.44	76.5101	506.4376	466.3325
cost/employee	**1088.944**	**167.2784**	**721.5697**	**1110.754**	**1259.195**	**124.5223**	**528.1158**	**893.5191**

State # (bin)	00101110	00101111	00110000	00110010	00110100	00110110	00111000	00111001
State # (dec)	46	47	48	50	52	54	56	57
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-7.79333	26.31449	12.24374	5.535432	-0.67179	-0.26118	35.03619	-1.43496
glprod	0.387872	1.304848	0.378912	1.554332	0.739432	1.165091	0.179754	0.227346
Totalcost	34203.05	15262.99	19093.65	8990.5	2102.64	11968.27	41615.58	10352.48
profit	0.465501	0.476582	0.323908	0.303031	0.04545	-0.06464	0.481137	0.685596
lprod	146910.3	168030.3	79112.49	359322.5	83298.7	274756.1	117122.1	133488.5
TTL_EMP	38.58973	27.53422	22.73745	36.57627	14.59969	17.49155	23.94273	19.06703
GRSPAYRL	1179958	1007677	462371.3	1165490	342470.2	470420.8	634523.3	727224
totalcost_pe	654.3456	341.2957	741.9933	160.9101	110.4387	77.49644	664.8722	131.5447
cost/employee	**886.3252**	**554.328**	**839.7444**	**245.8014**	**144.0195**	**684.2316**	**1738.13**	**542.9519**

State # (bin)	00111010	00111011	00111100	00111101	00111110	00111111	01000000	01000010
State # (dec)	58	59	60	61	62	63	64	66
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-1.02816	0.575741	-14.1634	1.300305	10.80128	4.189546	4.293678	1.258805
glprod	0.854503	-0.05478	0.592212	0.003651	0.144235	1.286239	0.747693	2.108144
Totalcost	131458.6	14225.88	38877.37	4052.43	15569.59	11376.43	12220.19	24307.84
profit	0.26139	0.195933	0.755436	0.213233	1.183219	0.246093	0.42208	0.35574
lprod	157197.4	113030.6	122820.4	92339.5	126988.6	140570.7	136627.2	208142.5
TTL_EMP	23.8957	25.12228	22.29043	16.62443	35.21479	19.15053	22.50513	91.36726
GRSPAYRL	870151.4	829102.1	527453.6	445912.7	1309843	505575.2	667372.6	3263022
totalcost_pe	1998.62	1940.32	1904.23	73.66819	191.5455	1383.12	546.2626	237.2419
cost/employee	**5501.347**	**566.2654**	**1744.128**	**243.7635**	**442.1322**	**594.0531**	**542.9957**	**266.0454**

State # (bin)	01000100	01000110	01001000	01001001	01001010	01001011	01001100	01001101
State # (dec)	68	70	72	73	74	75	76	77
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	42.99911	0.384061	0.276438	129.4075	2.143155	0.033374	2.833399	-0.55906
glprod	0.519456	-0.52938	-0.13866	4.928991	-0.21553	0.182635	0.960837	-0.56458
Totalcost	16031.11	13070.94	28541.78	497.9471	80426.45	1619129	90126.19	61889.39
profit	3.205217	0.129086	0.701023	**7.431458**	0.424302	0.119777	0.330431	0.076805
lprod	157080.2	80234.2	155935.8	435525.7	133024.7	195544.7	138132	90103.28
TTL_EMP	37.04453	22.88254	44.74752	90.94452	34.56766	366.6682	35.11817	36.52903
GRSPAYRL	1262651	958899.7	1393245	3566057	1268792	22115963	1582092	1358674
totalcost_pe	769.9881	55.06853	373.4728	14.22706	583.8958	2725.81	3252.1	165.136
cost/employee	**432.7524**	**571.2189**	**637.8404**	**5.475284**	**2326.639**	**4415.789**	**2566.369**	**1694.252**

State # (bin)	01001110	01001111	01010000	01011000	01011010	01011100	01011101	01011110
State # (dec)	78	79	80	88	90	92	93	94
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	2.973545	0.335432	2.699234	19.81379	-2.4382	-1.08478	-0.67286	14.07611
glprod	0.615035	-0.04959	4.563875	-0.23713	-0.46995	0.059072	-0.56724	-0.35676
Totalcost	194812.9	81671.58	4784.47	32631.07	73788.76	38959.83	324.3054	20683.57
profit	0.35966	-0.04275	0.76742	-0.056	0.197679	0.350882	-0.1629	0.131211
lprod	120262.5	136420.2	453336.8	79901.96	105347	173865	**62048.88**	86204.04
TTL_EMP	57.81497	67.98038	30.36488	32.80655	30.2625	63.13674	10.93577	42.77663
GRSPAYRL	2504899	2589704	913081.5	904310.5	1239284	2804341	389065.3	2080901
totalcost_pe	2048.61	355.7523	511.2946	728.9518	324.6691	464.9628	1.323696	47.35058
cost/employee	**3369.592**	**1201.399**	**157.5659**	**994.6511**	**2438.29**	**617.0706**	**29.65548**	**483.5249**

State # (bin)	01011111	01100000	01100010	01100100	01100110	01101000	01101010	01101100
State # (dec)	95	96	98	100	102	104	106	108
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-0.52056	-2.28188	2.822999	38.01782	0.513761	0.304679	44.07991	14.90989
glprod	0.590778	0.418746	-0.13456	0.201901	3.924801	0.63047	-0.24769	0.71888
Totalcost	56735.68	89420.34	14849.17	12416.95	632698.5	49887.69	584851.4	8865.33
profit	1.127216	0.356007	0.384738	1.910023	0.370997	0.107879	0.213498	2.035907
lprod	440005.2	188283.1	120631.8	153383.5	330932.7	153396.4	121993	200917.4
TTL_EMP	176.9651	60.16214	53.8046	110.1022	308.1719	66.97086	99.0792	45.42272
GRSPAYRL	8861329	2005575	1340433	2339770	18291932	1802434	2715133	1756456
totalcost_pe	245.4273	485.5941	81.0563	154.1689	4817.56	2820.71	20183.98	386.1898
cost/employee	**320.6039**	**1486.322**	**275.9833**	**112.7766**	**2053.07**	**744.9164**	**5902.867**	**195.1739**

State # (bin)	01101101	01101110	01101111	01110000	01111000	01111010	01111100	01111101
State # (dec)	109	110	111	112	120	122	124	125
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-1.05644	-2.78947	1.912344	0.744714	-70.5465	13.5624	8.477138	141.1509
glprod	0.179329	0.449592	-0.18202	1.27815	0.963878	0.294245	0.34535	3.844064
Totalcost	5337.37	90862.88	1930406	9196.52	96844.59	64780.14	13537.19	21851.79
profit	-0.10242	0.261232	0.457404	0.323078	2.081559	1.659121	0.795143	5.34635
lprod	77573.78	164740.8	173730.8	65381.75	157454.5	134596.5	87324.16	605005.7
TTL_EMP	23.57137	74.39308	160.4109	28.92811	66.45812	104.6818	48.98604	56.60851
GRSPAYRL	581668	2490234	7136338	447793.4	1580737	2136152	1449997	1868360
totalcost_pe	16.96015	1476.72	8114.33	393.2862	3957.39	231.7514	159.544	208.6618
cost/employee	**226.4345**	**1221.389**	**12034.14**	**317.9095**	**1457.227**	**618.8288**	**276.3479**	**386.016**

State # (bin)	01111110	01111111	10000000	10000001	10000010	10000011	10000100	10000101
State # (dec)	126	127	128	129	130	131	132	133
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	20.72218	-0.04804	11.58527	2.643812	**-2135.36**	-0.91355	9.62105	-0.19696
glprod	2.543099	-0.17031	1.478643	0.828359	1.831571	0.043568	0.800354	-0.2849
Totalcost	52617.86	31729.76	25986.96	49482.34	34319.49	3191.22	7881.65	52844.72
profit	0.498242	0.141274	0.647777	0.381463	0.541705	-0.02174	0.360644	0.330477
lprod	173042.1	104077.3	214663.2	178421.1	342936.4	224154.7	154056.1	133254.5
TTL_EMP	138.7417	73.60514	18.58286	55.15583	41.5922	29.63947	36.46372	70.67814
GRSPAYRL	6713391	2435686	802464.1	2345401	1874053	1433881	1345433	2914096
totalcost_pe	311.5535	328.605	2175.52	6759.35	498.24	297.8973	128.3262	866.1185
cost/employee	**379.2506**	**431.0808**	**1398.437**	**897.137**	**825.1425**	**107.6679**	**216.1505**	**747.6812**

State # (bin)	10000110	10000111	10001000	10001001	10001010	10001011	10001100	10001101
State # (dec)	134	135	136	137	138	139	140	141
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	7.056317	8.363975	3.102351	41.39965	-18.9902	3.627818	8.839984	0.433532
glprod	0.185461	0.239852	2.124774	1.629187	0.587666	0.868498	0.583921	1.698114
Totalcost	6820	92286.71	20452.1	10208.85	175304.4	80794.78	32247.48	7889729
profit	0.591976	0.726717	0.554962	1.038312	0.495046	0.295028	0.7341	0.460278
lprod	139187.7	213749.8	268172.8	224234.6	213668.6	401858.3	228488.2	383627.8
TTL_EMP	50.34267	86.37632	37.41143	38.70259	41.66007	48.92372	45.06553	68.79292
GRSPAYRL	2119238	4211889	1753688	2088979	1837333	2337891	2282766	4266583
totalcost_pe	44.69783	955.0409	594.8621	369.1588	1713.74	371.8097	905.3483	1951767
cost/employee	**135.4716**	**1068.426**	**546.6805**	**263.7769**	**4207.971**	**1651.444**	**715.5687**	**114688.1**

State # (bin)	10001110	10001111	10010000	10010001	10010010	10010100	10010101	10010110
State # (dec)	142	143	144	145	146	148	149	150
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	6.494563	-0.1356	3.160646	-6.36909	-1.15854	-1.79924	-1.02943	4.113902
glprod	3.464042	1.080342	2.002381	10.57489	3.459761	1.020464	-0.15275	0.456959
Totalcost	54921.77	76846.33	18938.09	1221820	11736.32	65345.34	12559.57	124925.9
profit	1.119612	0.127667	0.927747	0.248824	0.121611	0.113916	0.074238	0.158296
lprod	297254.1	238895.9	322727.4	366058.9	**1091579**	177204.7	146368.6	144798.7
TTL_EMP	73.72882	74.93532	35.42752	82.6077	26.52177	22.12881	37.6796	97.17546
GRSPAYRL	4134494	3097960	2153426	3462504	1160908	506107.2	2613436	3762459
totalcost_pe	657.9609	1416.04	840.4836	81454.65	83.53139	1865.1	1521.89	868.0086
cost/employee	**744.9159**	**1025.502**	**534.5587**	**14790.63**	**442.5164**	**2952.953**	**333.3254**	**1285.571**

State # (bin)	10011000	10011001	10011010	10011011	10011100	10011101	10011110	10011111
State # (dec)	152	153	154	155	156	157	158	159
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	5.918499	4.481269	2.517171	44.51082	1.52836	-0.50019	4.948161	23.26598
glprod	0.99198	0.232524	0.555554	2.224482	0.683907	1.411849	0.453801	0.322458
Totalcost	12929.26	35036.27	40717.65	42100.53	210489.7	173134	53273.35	36349
profit	0.215736	0.089994	1.455488	0.371661	0.302264	0.342468	0.370274	2.215158
lprod	216772.6	150446.2	263068.9	347770.2	185375.1	242738.3	314244.6	219890.2
TTL_EMP	29.52061	20.14665	41.74575	77.31277	59.1907	120.4861	102.0576	37.68676
GRSPAYRL	1251639	861142.6	1895694	3584289	3946656	6869800	5070359	1617846
totalcost_pe	704.5593	2601.12	317.4503	560.891	1357.92	571.8943	311.84	885.868
cost/employee	**437.974**	**1739.062**	**975.3723**	**544.5482**	**3556.128**	**1436.962**	**521.9932**	**964.5032**

State # (bin)	10100000	10100001	10100010	10100100	10100110	10100111	10101000	10101001
State # (dec)	160	161	162	164	166	167	168	169
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	32.02898	0.950289	0.503731	1.548792	19.03246	40.50821	-11.9313	-30.7053
glprod	1.862206	0.605307	0.786708	3.685004	1.318269	0.808003	0.975437	0.336791
Totalcost	36009.57	77194.92	95705.87	9666.14	31421.76	21567.61	38842.06	18305.83
profit	0.58677	0.119621	0.487416	0.976005	0.427344	0.919647	0.465909	1.048347
lprod	245547.3	262338.1	189997.6	362246.7	471208.2	229594.8	209976.8	256045.4
TTL_EMP	41.98595	92.31538	66.406	36.64823	56.39037	145.3252	39.68501	53.03369
GRSPAYRL	1972073	4363093	3069499	1714967	2708774	6239787	1618256	3389152
totalcost_pe	428.7998	2723.84	1007.7	241.9824	519.6226	56.21793	635.2846	439.8621
cost/employee	**857.6575**	**836.2086**	**1441.223**	**263.7546**	**557.2186**	**148.4093**	**978.759**	**345.1736**

State # (bin)	10101010	10101011	10101100	10101101	10101110	10101111	10110000	10110010
State # (dec)	170	171	172	173	174	175	176	178
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	11.97712	**744.8604**	6.094194	0.116003	-0.75901	30.49497	21.10688	4.481702
glprod	1.231327	0.756005	1.706094	1.058988	1.317923	0.451618	1.568842	0.542096
Totalcost	36921.21	6025.78	37131.36	20094.08	64716.93	457871.3	17085.36	29977.36
profit	0.721764	0.774571	0.945109	0.416714	2.329583	1.191981	0.671264	0.366736
lprod	220258.1	223059.5	321986.6	197060.7	204761.2	201513.6	216237.6	184874.3
TTL_EMP	57.3574	17.58157	53.87151	53.53827	49.33325	85.26501	42.48481	84.84717
GRSPAYRL	2444797	755971.3	2807413	2034938	2094578	3515120	1834232	3366346
totalcost_pe	639.7558	65.85052	384.3213	602.3647	1595.95	1315.7	276.4184	291.8231
cost/employee	**643.7044**	**342.7329**	**689.2578**	**375.3218**	**1311.832**	**5369.979**	**402.1522**	**353.3101**

State # (bin)	10110011	10110100	10110110	10110111	10111000	10111001	10111010	10111011
State # (dec)	179	180	182	183	184	185	186	187
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	300.4621	-0.55789	-7.33217	2.87861	-2.48872	-3.50912	-3.76495	8.9118
glprod	5.703315	1.135576	1.894067	0.661772	1.218562	2.529991	1.612361	3.135666
Totalcost	1856572	6517.44	72040.5	107060.7	280826	64426.18	250573.4	2695.18
profit	5.432468	0.12911	0.959212	0.323639	0.531275	0.257193	0.350859	0.300211
lprod	710183.3	203913	291697.3	166093	230900.3	162370.2	216381.9	252256
TTL_EMP	150.0352	26.40568	60.26007	71.81635	40.5831	37.55609	47.13237	41.86578
GRSPAYRL	7413951	1215438	1939809	3867441	1489869	1941268	1863628	1902769
totalcost_pe	7015.76	187.1767	368.1528	1224.72	41015.03	996.2436	3408.02	39.49805
cost/employee	**12374.24**	**246.8196**	**1195.493**	**1490.757**	**6919.777**	**1715.466**	**5316.376**	**64.37669**

State # (bin)	10111100	10111101	10111110	10111111	11000000	11000001	11000010	11000100
State # (dec)	188	189	190	191	192	193	194	196
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	16.37172	-40.0373	0.756418	1.919647	161.1885	-0.59655	0.251313	3.625706
glprod	1.54358	0.73158	0.708952	3.531251	1.612682	-0.35614	0.288429	0.162832
Totalcost	31001.48	13936.69	47304.66	33451.65	22654.29	37806.95	48659.37	41203.42
profit	1.513421	1.151824	0.43832	0.42942	0.696253	0.072352	0.396714	0.152451
lprod	264337.9	189479.2	205182.9	195649.3	206527.3	316812.4	215390.2	121250.1
TTL_EMP	32.86559	32.25585	60.45862	37.08005	20.03654	423.2417	68.07219	62.10148
GRSPAYRL	1406295	1382004	2554780	1669444	740499	19614133	2979019	2213216
totalcost_pe	448.6475	152.3437	570.5456	1069.75	1963.11	133.5935	500.7288	1206.01
cost/employee	**943.2809**	**432.0671**	**782.4304**	**902.1469**	**1130.649**	**89.32708**	**714.8201**	**663.4853**

State # (bin)	11000101	11000110	11001000	11001001	11001010	11001100	11001101	11001110
State # (dec)	197	198	200	201	202	204	205	206
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	2.263188	12.25493	3.915313	54.13302	9.505092	17.4299	-0.72833	6.189778
glprod	0.172348	0.046988	0.921543	2.689009	-0.08687	-0.11481	0.441373	2.059946
Totalcost	18680.61	11205.91	54632.16	62603.17	54288.98	29641.75	110745	198219.8
profit	2.351264	0.654757	0.844139	2.973169	0.186481	1.293007	0.465032	1.154828
lprod	291978.4	132694	227128.6	191067.3	157750	187192.4	216582.6	283688.3
TTL_EMP	232.8349	45.33017	46.1169	60.14285	42.00564	44.39003	157.6568	78.66623
GRSPAYRL	12162655	2247496	1958528	2521121	1562786	1721814	10385362	4168715
totalcost_pe	587.9213	50.31226	2037.33	3733.19	956.8886	410.7871	640.034	1889.23
cost/employee	**80.23115**	**247.2064**	**1184.645**	**1040.908**	**1292.421**	**667.7569**	**702.4438**	**2519.757**

State # (bin)	11001111	11010000	11010010	11010110	11011000	11011010	11011100	11011101
State # (dec)	207	208	210	214	216	218	220	221
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	0.614044	-0.44293	-2.21684	31.32256	-5.06467	0.469678	8.035431	-0.37024
glprod	0.042603	1.697402	0.778753	0.470087	2.79218	0.092097	0.710534	-0.18139
Totalcost	93066.48	31807.23	203036.4	283113.7	50746.47	203448.5	289757.8	76621.72
profit	0.184199	0.297621	0.241409	0.504338	-0.14607	2.633164	0.43864	0.108772
lprod	175030	358994.2	225953.9	185457.9	121105.6	191801.3	151262.3	110502.9
TTL_EMP	149.6124	72.3418	139.4573	339.4475	29.19712	92.67159	87.89839	46.8783
GRSPAYRL	6481419	3557707	5456255	13548704	1244279	4196432	5645971	3060751
totalcost_pe	496.653	429.0187	1509.47	420.6597	1151.18	353.3229	2348.12	83.43001
cost/employee	**622.0506**	**439.6798**	**1455.903**	**834.0427**	**1738.064**	**2195.371**	**3296.509**	**1634.482**

State # (bin)	11011110	11011111	11100000	11100001	11100010	11100100	11100110	11101000
State # (dec)	222	223	224	225	226	228	230	232
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
gprofit	0.215935	15.61578	2.077719	9.591406	-1.78741	7.479948	2.161592	3.29
glprod	0.720846	**-0.7036**	1.088756	4.265264	0.890672	0.428709	0.382078	0.904276
Totalcost	66304.43	17088.22	19702.44	17656.54	60841.29	2882.04	298106.1	45561.96
profit	0.220993	2.411488	1.109181	0.033621	0.863158	1.181464	0.383932	0.421387
lprod	279726.6	176051.3	205004.4	394464.5	162418.6	209971.5	227358.5	228704.4
TTL_EMP	163.4484	47.48263	39.32607	123.8397	54.23796	34.37778	176.4188	51.30274
GRSPAYRL	8891298	1278792	1416291	6913611	2130820	1092859	10925705	1756912
totalcost_pe	153.2135	346.1334	300.3856	166.5712	714.0645	61.44627	1871.18	464.9226
cost/employee	**405.6598**	**359.8836**	**501.002**	**142.5758**	**1121.747**	**83.83437**	**1689.763**	**888.0999**

State # (bin)	11101010	11101011	11101100	11101101	11101110	11101111	11110000	11110100
State # (dec)	234	235	236	237	238	239	240	244
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	142.3621	1.011967	13.41345	-0.3043	398.3543	-0.20501	-1.32172	0.796988
glprod	1.211156	-0.44883	1.35258	0.861379	5.642903	1.544238	0.826173	3.006575
Totalcost	164811.3	27003.87	42057.59	9110.11	35767.37	347429.8	46498.47	195617.6
profit	2.748946	0.127494	1.387421	-0.20815	4.297605	0.91841	0.279043	0.265644
lprod	289249.9	179925.4	358430.5	81164.53	362784.9	162310	111937.1	178471.5
TTL_EMP	51.06734	108.1855	55.47692	23.07537	52.7552	64.17599	93.64884	58.65473
GRSPAYRL	1953496	3698407	2518610	565295.3	2182005	2546880	3290677	2976762
totalcost_pe	5890.44	156.2997	590.3888	1191.22	486.2264	598.2032	538.9275	5768.25
cost/employee	**3227.332**	**249.6072**	**758.1097**	**394.798**	**677.9876**	**5413.704**	**496.5195**	**3335.07**

State # (bin)	11111000	11111001	11111010	11111011	11111100	11111101	11111110	11111111
State # (dec)	248	249	250	251	252	253	254	255
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
gprofit	-15.5752	-25.253	3.683131	46.53914	-6.03383	4.97924	3.94473	4.409711
glprod	2.783055	5.711067	0.082394	2.30448	0.963886	2.376259	-0.27831	**11.53608**
Totalcost	365212.9	61361.05	784440	0	11073.98	28732.9	17957.86	51741.71
profit	0.625095	1.150342	1.420609	1.033472	0.57453	1.832269	0.203998	0.565595
lprod	249406.1	260717.3	127338.8	336895.2	179347.3	212787.3	118613.1	292907.7
TTL_EMP	66.23297	61.95463	90.90608	105.1718	55.77989	28.08198	78.54291	50.65771
GRSPAYRL	1910220	2583900	3228843	5051643	2091958	915089.7	3515363	2211544
totalcost_pe	1080.2	1914.59	8131.59	0	294.6612	890.643	226.4419	1594.9
cost/employee	**5514.064**	**990.419**	**8629.126**	**0**	**198.53**	**1023.179**	**228.6376**	**1021.398**

Table 101. State Means (Computer Use and Human Resource Management Practices)

	Start State	Min Value	Max State	Max Value	Optimal Path
gprofit	130	-2135.36	171	744.86043	130-131-139-171
glprod	223	-0.703601	255	11.536082	223-255
profit	25	-0.224475	73	7.4314578	25-9-73
lprod	93	62048.88	146	1091578.6	93-29-157-153-152-154-146

Table 102. Start State, the start states associated minimum performance value, the maximum state, the maximum states associated performance value, and the optimal path from start state to the highest attainable performance state (Computer Use and Human Resource Management Practices).

Appendix C. Additional Information (variable names, etc.)

C.1 For analysis by industry:

Variable descriptions:
Totalcost = total costs for implementing technologies.
gprofit = % change in profit from previous year to current year.
lprod = % change in production level in the last year
Tech1 = implement new hardware/software? (1=yes)
Tech23 = implement other technology? (1 = yes)
TTL_EMP = total number of employees employed (received T4 slip)
Proc Prod = New product or process innovation introduced? (1 = yes)
TTL_EMPBI = Total # employees higher than industry average? (1=yes)
TRNG_EXPN = Total training expenditure
TRNG_EXPBI = Is average training expenditure per employee higher than industry average? (1=yes)
Tech2 = Implemented new computer controlled/assisted technology?
Tech 3 = Implemented other technology?
REVENUE = total revenue
GRSPAYRLBI = average gross salary per employee higher than industry average?
TotaletrainBI = Is average number of employees trained for new technology higher than industry average?
TotaldtrainBI = Is the duration of training for new technology greater than the industry average?
SAL_EXPNBI = Is the average non-wage benefits per employee higher than industry average?
SAL_EXPN = average non-wage benefits per employee
GRSPAYRL = gross payroll
Totaletrain = Total # of employees trained for new technology
Totaldtrain = Total duration of training for new technologies

The order of the binary variables is as follows:
Tech1, Tech23, TTL_EMPBI, ProcProd, & TRNG_EXPBI

C2. For the rest of the analysis:

gprofit: **% Change in profit from previous year**

glprod: **% Change in labor productivity from previous year**

Totalcost: **Total costs of updgrading or new technology**

Profit: **Profit**

Lprod: **labor productivity**

TTL_EMP: **Total number of empoyees**

GRSPAYRL: **Gross payroll**

Tech1: **implementation of new software/hardware**

Tech2: **implementation of computer controlled/assisted technology**

Tech3: **Other technology**

NewProc: **New Process improvement**

NewProd: **New Product improvement**
FirstInn: **Innovation that is First in Country or world**
totalcost_pe: **Total technology costs divided by number of employees**
TechUse: **Employee uses computer controlled/assisted technology**
CompUse: **Employee uses computer**
HRM1: **Employee Suggestion Program**
HRM2: **Flexible Job Design**
HRM3: **Information Sharing with employees**
HRM4: **Problem Solveing Teams**
HRM5: **Joint labor-management committees**
HRM6: **Self-directed work groups**
Educ: **Highest level of education achieved**
ClassTrain: **Employee received (in the past year) Formal Training in the classroom**
JobTrain: **Employee received (in the past year) on-the-job training**
HelpTrain: **Employee received (in the past year) aid from employer for training outside of work that is not directly related to his/her job**
NoHelpTrain: **Employee received (in the past year) training for work w/o the aid of the employer**

Appendix D. 4-Variable CSPP Problem Example

The following example is taken from analysis of 4 groups of technologies from a linked dataset involving the 1998 Survey of Advanced Technology in Canadian Manufacturing, the 1998 Annual Survey of Manufactures and the 1995 Annual Survey of Manufactures. In this example, we assume the firm is currently in state 0011 (i.e. 3 in decimal notation). First we need to determine the mean profit values for each set of firms working with each state of technology implementation in the electronics industry. Table 99 lists these values.

State Variables		Mean Profit (in CAD $'s)
Binary	Decimal	
0000	0	79051
0001	1	2465
0010	2	69510
0011	3	52109
0100	4	-6682
0101	5	187452
0110	6	-43410
0111	7	-6314
1000	8	-2415
1001	9	18985
1010	10	9507
1011	11	81881
1100	12	69560
1101	13	103116
1110	14	295011
1111	15	26762

Table 103. Mean profit for all firms in each state of technology use.

The same values can be plotted out as shown in Figure 12.

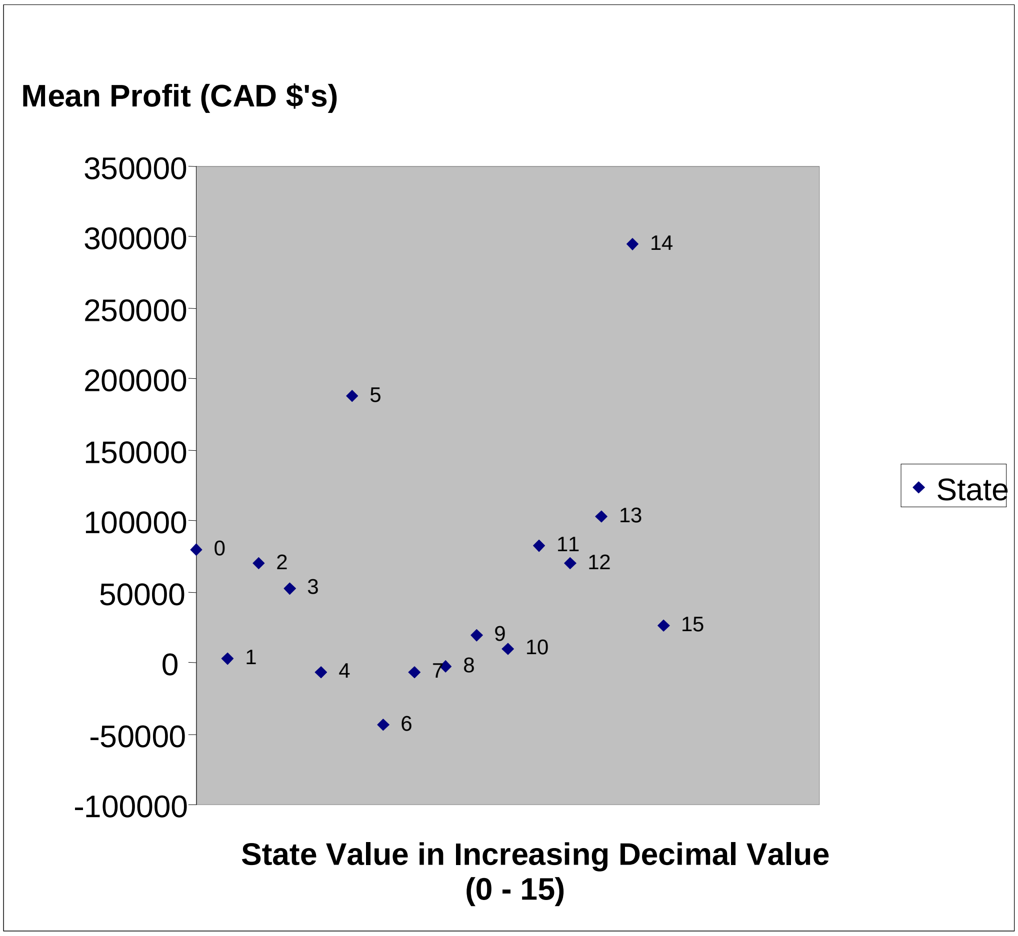

Figure 12. Mean profit values for design and engineering and business practice factor state in the Canadian chemical industry

We want to find a path from state 3 (i.e. 0011) to the state with the highest mean profit, which happened to be state 14 (i.e. 1110) by making single additions or removals of factor implementations.

For this problem, we suppose that since the manager thinks he can only handle making one change to his organization at a time, this limits the number of moves a manager can make at any given state, that being four. For example, being in state 0011, the manager can move to state 1011, 0111, 0001, or 0010. Thus the graphical representation of arcs (undirected) that are associate with the states can be illustrated as in Figure 13.

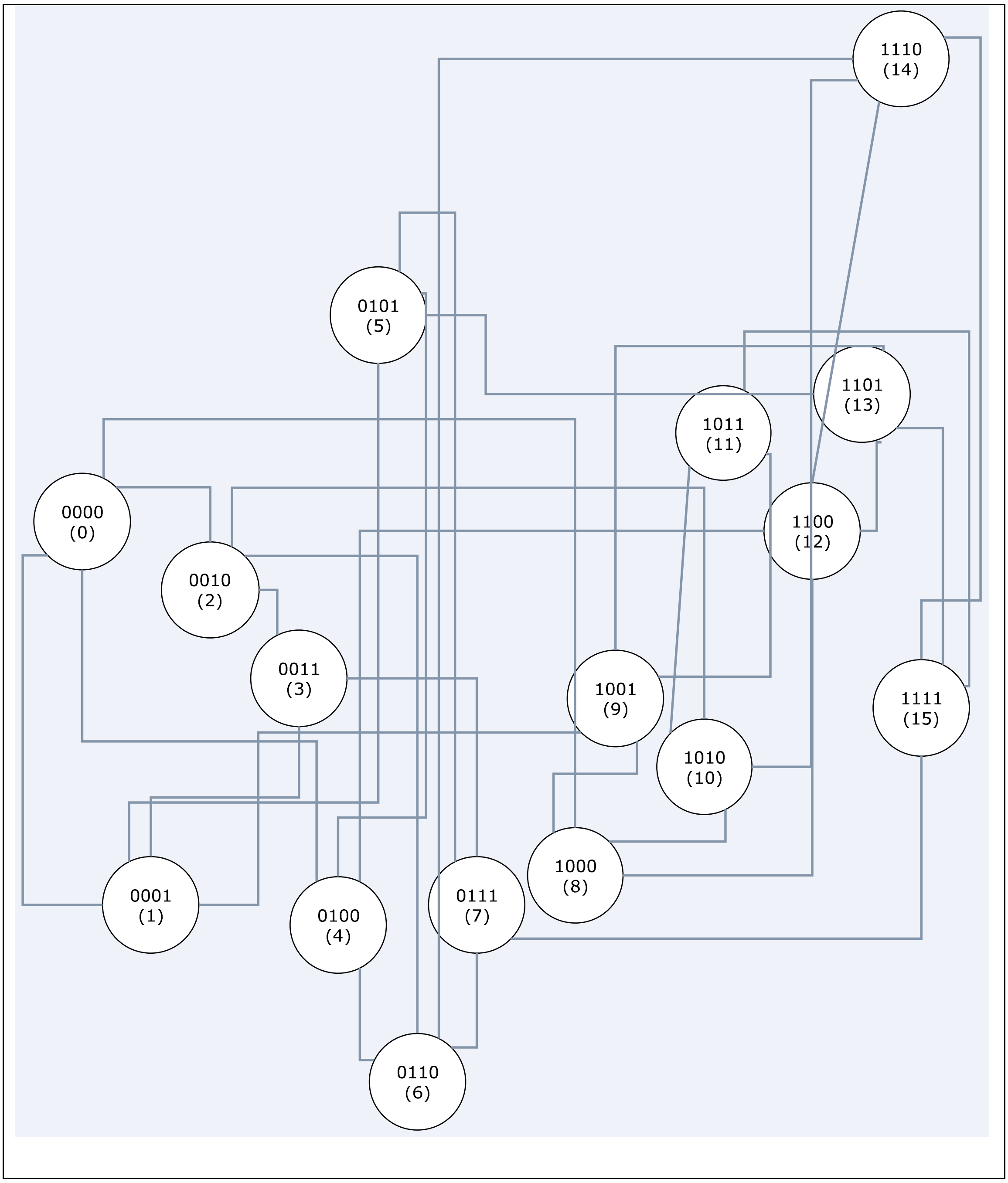

Figure 13. Graphical representation of the state network diagram for the example.

More data is needed before we can model this problem. First, we have resource constraints given by the manger of the firm. The first involves a budget of $ dollars to spend on making all the necessary changes to maximize his profit. Second, there is an estimated time constraint on adding or removing the given technologies and practices. And finally, the manager has his own preferences on which changes and additions he prefers to make, given in a value between 0 and 1. This preference value will be the main value that the manager would like to minimize when making the step-by-step additions and subtractions of state factors. So given the standard Constrained Shortest Path Integer Program (CSPIP),

CSPIP $z^* = \min_{\mathbf{x}} \mathbf{c}x \quad (1)$

$$\text{s.t. } A\mathbf{x} = \mathbf{b} \quad (2)$$

$$F\mathbf{x} \leq \mathbf{g} \quad (3)$$

$$\mathbf{x} \geq \mathbf{0}\ ,\ x_{uv} \in \{0,1\}, \quad (4)$$

the associated objective values, c, are the preference values given by the manager and is shown in Table 100. The table also show the values for F, the resource constraints of budget and time. In addition the constraint on the budget is $25 million and the constraint on time to implement all changes associated to the implementation/removal of technologies is 2 years, respectively. This is represented in the vector $\mathbf{g}$=$[25\ 2]^T$ in the model.

Edge (state to state)	c-values (preference)	F(1) (budget, millions of CAD $'s)	F(2) (time, years)
0-1	0.869216	18.97188	0.799383
0-2	0.833282	13.41327	0.471995
0-4	0.78929	19.02507	0.717416
0-8	0.498684	17.99716	0.07603
1-0	0.847397	16.13657	0.180287
1-3	0.612935	17.1265	0.378948
1-5	0.931412	9.484101	0.22088
1-9	0.080106	11.58132	0.747517
2-0	0.052425	6.348714	0.519815
2-3	0.981758	17.92956	0.162986
2-6	0.330697	9.074334	0.254378
2-10	0.322484	0.063218	0.057305
3-1	0.756757	8.202517	0.149292
3-2	0.869926	2.769449	0.417873
3-7	0.475986	13.1946	0.488591
3-11	0.584387	3.541956	0.132162
4-0	0.864614	12.79487	0.807192
4-5	0.135185	0.960383	0.865578
4-6	0.25852	10.76398	0.975799
4-12	0.277573	16.72083	0.364079
5-1	0.16445	13.91132	0.234852
5-4	0.968736	0.615057	0.687692
5-7	0.417448	2.434531	0.309226
5-13	0.13402	16.00468	0.72463
6-2	0.171665	6.234626	0.277884
6-4	0.647792	9.441129	0.029453
6-7	0.728789	15.2771	0.914831
6-14	0.495216	19.51879	0.695017
7-3	0.659941	13.73278	0.330259
7-5	0.276901	0.963484	0.197621
7-6	0.919974	9.90935	0.585916
7-15	0.609684	9.983453	0.089939
8-0	0.060014	17.29942	0.767504
8-9	0.817518	15.63905	0.589815
8-10	0.642664	17.3208	0.694701
8-12	0.898832	10.73105	0.653429
9-1	0.815975	1.896838	0.737489
9-8	0.628714	1.489718	0.655622
9-11	0.417413	1.09448	0.579457
9-13	0.307423	1.937416	0.69452
10-2	0.05866	19.54889	0.07726
10-8	0.215237	14.66626	0.858418
10-9	0.226861	0.268093	0.596864

10-14	0.827514	17.26176	0.469978
11-3	0.764751	17.38979	0.918202
11-9	0.161649	11.69882	0.952894
11-10	0.49974	8.230815	0.501802
11-15	0.124558	9.099461	0.502214
12-4	0.467357	19.40391	0.803967
12-8	0.053279	9.674356	0.433283
12-13	0.835337	1.786421	0.884826
12-14	0.330172	3.043832	0.627527
13-5	0.65015	14.19899	0.691834
13-9	0.720949	11.61079	0.783054
13-12	0.847012	7.768194	0.988716
13-15	0.988457	12.73959	0.765444
14-6	0.706117	18.29865	0.956899
14-10	0.126921	7.746147	0.142264
14-12	0.422453	17.25879	0.063502
14-15	0.543754	4.209046	0.370329
15-7	0.217323	15.58529	0.063086
15-11	0.713675	18.2178	0.61284
15-13	0.743458	5.24061	0.711338
15-14	0.180891	5.424091	0.75553

Table 104. Values for c and F in the example.

The transposed (in order to fit it on the page) vertex-edge incidence matrix, A^T, where the vertices represent the states and the edges represent the state to state changes is shown below.

	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
0-1	1	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0-2	1	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0
0-4	1	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0
0-8	1	0	0	0	0	0	0	0	-1	0	0	0	0	0	0	0
1-0	-1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1-3	0	1	0	-1	0	0	0	0	0	0	0	0	0	0	0	0
1-5	0	1	0	0	0	-1	0	0	0	0	0	0	0	0	0	0
1-9	0	1	0	0	0	0	0	0	0	-1	0	0	0	0	0	0
2-0	-1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
2-3	0	0	1	-1	0	0	0	0	0	0	0	0	0	0	0	0
2-6	0	0	1	0	0	0	-1	0	0	0	0	0	0	0	0	0
2-10	0	0	1	0	0	0	0	0	0	0	-1	0	0	0	0	0
3-1	0	-1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
3-2	0	0	-1	1	0	0	0	0	0	0	0	0	0	0	0	0
3-7	0	0	0	1	0	0	0	-1	0	0	0	0	0	0	0	0
3-11	0	0	0	1	0	0	0	0	0	0	0	-1	0	0	0	0

4-0	-1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
4-5	0	0	0	0	1	-1	0	0	0	0	0	0	0	0	0	0
4-6	0	0	0	0	1	0	-1	0	0	0	0	0	0	0	0	0
4-12	0	0	0	0	1	0	0	0	0	0	0	0	-1	0	0	0
5-1	0	-1	0	0	0	1	0	0	0	0	0	0	0	0	0	0
5-4	0	0	0	0	-1	1	0	0	0	0	0	0	0	0	0	0
5-7	0	0	0	0	0	1	0	-1	0	0	0	0	0	0	0	0
5-13	0	0	0	0	0	1	0	0	0	0	0	0	0	-1	0	0
6-2	0	0	-1	0	0	0	1	0	0	0	0	0	0	0	0	0
6-4	0	0	0	0	-1	0	1	0	0	0	0	0	0	0	0	0
6-7	0	0	0	0	0	0	1	-1	0	0	0	0	0	0	0	0
6-14	0	0	0	0	0	0	1	0	0	0	0	0	0	0	-1	0
7-3	0	0	0	-1	0	0	0	1	0	0	0	0	0	0	0	0
7-5	0	0	0	0	0	-1	0	1	0	0	0	0	0	0	0	0
7-6	0	0	0	0	0	0	-1	1	0	0	0	0	0	0	0	0
7-15	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	-1
8-0	-1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
8-9	0	0	0	0	0	0	0	0	1	-1	0	0	0	0	0	0
8-10	0	0	0	0	0	0	0	0	1	0	-1	0	0	0	0	0
8-12	0	0	0	0	0	0	0	0	1	0	0	0	-1	0	0	0
9-1	0	-1	0	0	0	0	0	0	0	1	0	0	0	0	0	0
9-8	0	0	0	0	0	0	0	0	-1	1	0	0	0	0	0	0
9-11	0	0	0	0	0	0	0	0	0	1	0	-1	0	0	0	0
9-13	0	0	0	0	0	0	0	0	0	1	0	0	0	-1	0	0
10-2	0	0	-1	0	0	0	0	0	0	0	1	0	0	0	0	0
10-8	0	0	0	0	0	0	0	0	-1	0	1	0	0	0	0	0
10-9	0	0	0	0	0	0	0	0	0	-1	1	0	0	0	0	0
10-14	0	0	0	0	0	0	0	0	0	0	1	0	0	0	-1	0
11-3	0	0	0	-1	0	0	0	0	0	0	0	1	0	0	0	0
11-9	0	0	0	0	0	0	0	0	0	-1	0	1	0	0	0	0
11-10	0	0	0	0	0	0	0	0	0	0	-1	1	0	0	0	0
11-15	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	-1
12-4	0	0	0	0	-1	0	0	0	0	0	0	0	1	0	0	0
12-8	0	0	0	0	0	0	0	0	-1	0	0	0	1	0	0	0
12-13	0	0	0	0	0	0	0	0	0	0	0	0	1	-1	0	0

12-14	0	0	0	0	0	0	0	0	0	0	0	0	1	0	-1	0
13-5	0	0	0	0	0	-1	0	0	0	0	0	0	0	1	0	0
13-9	0	0	0	0	0	0	0	0	0	-1	0	0	0	1	0	0
13-12	0	0	0	0	0	0	0	0	0	0	0	0	-1	1	0	0
13-15	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	-1
14-6	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	1	0
14-10	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	1	0
14-12	0	0	0	0	0	0	0	0	0	0	0	0	-1	0	1	0
14-15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	-1
15-7	0	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	1
15-11	0	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	1
15-13	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	0	1
15-14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	1

Also, b^T = [0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0] since we are starting at state 3 and want to end in state 14. So we want all edges to have a total flow of 0 (meaning if we move to any of these states, we want to also leave the state) except for the starting state we only want to leave it once and never return and the ending state we only want to enter and stop.

Given this information, we may now relax the constraints of the problem, as in the proposal,

$$z^* \geq \underline{z}(\lambda) = \min_{\mathbf{x}} \mathbf{c}x + \boldsymbol{\lambda}(F\mathbf{x} - \mathbf{g}) \qquad (5)$$

$$\text{s.t. } A\mathbf{x} = \mathbf{b} \qquad (6)$$

$$\mathbf{x} \geq \mathbf{0}, \; x_{uv} \in \{0,1\}, \qquad (7)$$

and create the Constrained Shortest Path Lagrangian Relaxation problem.

$$\textbf{CSPLR}\quad z^* = \max_{\lambda \geq 0} \underline{z}(\lambda) \tag{8}$$

$$= \max_{\lambda \geq 0} \min_{\mathbf{x}} (\mathbf{c} + \lambda F)\mathbf{x} - \lambda \mathbf{g} \tag{9}$$

$$\text{s.t. } A\mathbf{x} = \mathbf{b} \tag{10}$$

$$\mathbf{x} \geq \mathbf{0},\ x_{uv} \in \{0,1\}, \tag{11}$$

To run the Lagrangian relaxation and enumeration algorithm, we must first choose an initial **x** and ***λ*.** For this problem, we may choose any $\boldsymbol{\lambda} \geq \mathbf{0}$ **(**we use [2 2] in this example) and any path from state 3 to state 14 (say 3-2-6-14) represented as x = [0 0 1 1 0 0 1 0 0 0 0 0 0 0 1 0]. Once the subgradient optimization algorithm converges to a solution resulting in a feasible upper and optimal lower objective function value bounds, the path enumeration algorithm keeps filtering through paths and reduces the upper bound whenever a better path (one with lower objective value than the current upper bound) is found. This keeps going until the optimal solution is discovered.

When running this algorithm on the example using MATLAB 7.3, the result was verified using the built-in function **bintprog** found in MATLAB's Optimization Toolbox. **bintprog** is specifically used to solve binary integer problems, and was run on the original CSPIP formulation. It uses an LP-relaxation-based branch-and-bound algorithm.

The solution resulting from both approaches came up with the same solution (LRE algorithm completed in 0.3298 seconds and **bintprog** in 0.2866 seconds), with $x_i = 1$ for *i=(3,11), (11,15), (15,14)* and $x_i = 0\ \ \forall x_i \in E \setminus \{(3,11), (11,15), (15,14)\}$. This represents starting with the state 0011 (where more than the average amount of the business practices listed BP Factor 2 and BP Factor 3, respectively, are currently implemented), then moving to state 1011 (implementing more than the average amount of DES technologies), then moving to state 1111 (adding more than the average amount of the business practices listed BP Factor 1), and finally moving to state 1110 (removing enough business practices from BP Factor 3 to below the electronics industry average. This results in minimizing the manger’s preference level value at z*= 0.8898, while keeping the budget and time constraints in tact at $18.0655 million (< $25 million) and 1.3899 years (< 2 years), respectively. The resulting shortest path is shown in Figure 14.

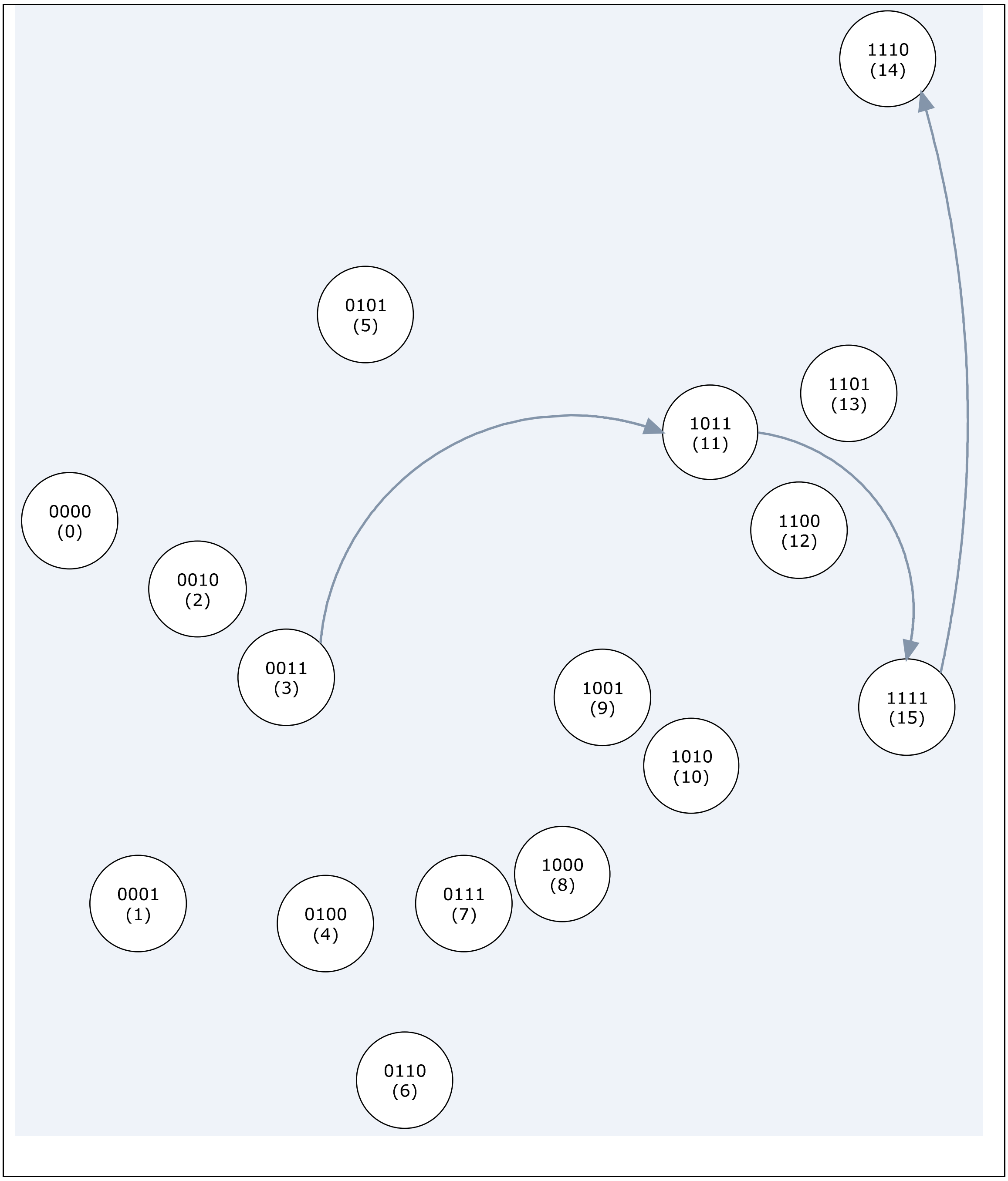

Figure 14. The shortest constrained path from state 3 to state 14 for the example