12-31-1990

A proposed model for comparing the performance of neural networks and statistical approaches in predicting project profits of an asphalt paving company

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ABSTRACT

A Proposed Model for Comparing the Performance of Neural Networks and Statistical Approaches in Predicting Project Profits of an Asphalt Paving Company

by

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It is currently assumed that the performance of a model for predicting project profits of an asphalt paving company varies with an unknown number of parameters. An earlier study indicates that the parameters are not well understood (Berry, 1990). A search of the literature suggests that the available models usually are described by those who develop and use them as universally reliable and valid tools for solving complex problems (Allman, 1989; Bumke, 1988; Clark, 1988; Cohen & Howe, 1988; Fillon, 1989; Kling, 1990; Lawrence, Petterson, & Hartzberg, 1990; Marose, 1990; Pollak, 1988; Reynolds, 1988; Sullivan & Reeve, 1988; Thurber, 1988). Present models such as neural networks and advanced statistical approaches have been promoted as being capable of augmenting, or even supplanting, human decision-making. Yet, little research published to date compares the results of these two different models (Caudill, 1990). Few works published to date establish any criteria for evaluating the results provided by these models.

It is the author's belief that neural network models must be subjected to the same rigorous

quantitative and qualitative evaluation that statistical models have endured.

This author believes that the importance of a quantitative metric for measuring the relative accuracy, reliability and validity of the results of each model is apparent. What is less apparent are the qualitative factors, including perceived accuracy, perceived reliability and perceived validity of each model, usability issues, and the cognitive styles of those using the models.

A PROPOSED MODEL FOR COMPARING THE PERFORMANCE OF NEURAL NETWORKS AND STATISTICAL APPROACHES IN PREDICTING PROJECT PROFITS OF AN ASPHALT PAVING COMPANY

by
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A Thesis
Submitted to the Faculty of the Graduate Division of
the New Jersey Institute of Technology
in Partial Fulfillment of the Requirements for the
Degree of Master of Science
Department of Industrial and Management Engineering
December 1990

APPROVAL PAGE

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This thesis is dedicated to
Dr. Daniel C. Foss

ACKNOWLEDGEMENT

The author wishes to express her sincere gratitude to her advisor, Professor Gordon Kalley, for his guidance, friendship, and moral support throughout this research.

Special thanks to Professor Carl Wolf serving as member of the Committee.

The author is grateful to Professor Carl Wolf for his suggestions and especially for his help in locating data appropriate for this research.

Thank you to the asphalt paving company which supplied some of the data. Thank you to Douglas Berry for his help in obtaining this data, and for sharing his experiences in the asphalt paving business.

TABLE OF CONTENTS

Page

1. INTRODUCTION. 1

1.1 Background. 1

1.1.1 Company and Problem Features 1

1.2 Review of the Literature. 5

1.2.1 Introduction 5

1.2.2 Review of the Literature 7

1.2.3 Summary. 34

1.3 Brief Statement of the Problem. 35

2. THE NEURAL NETWORK MODEL. 41

2.1 General Characteristics 41

2.2 Theoretical Considerations. 54

2.3 The Development of This Profit Model. . . . 55

2.4 Summary of Major Findings 60

2.5 Discussion. 61

3. THE STATISTICAL MODEL 83

3.1 General Characteristics 83

3.2 Theoretical Considerations. 93

3.3 The Development of This Profit Model. . . . 93

3.4 Summary of Major Findings 97

3.5 Discussion. 97

4. COMPARATIVE ANALYSIS. 105

4.1 Introduction. 105

4.2 Quantitative Approaches 105

4.2.1 Introduction 105

4.2.2 Return on Investment (ROI) 105

4.2.3 Sassone's Hedonic Approach 106
4.2.4 Reliability. 108
4.2.5 Validity 108
4.2.6 Summary. 109
4.3 Qualitative Approaches. 109
4.3.1 Introduction 109
4.3.2 Usability Issues 110
4.3.3 Cognitive Styles 111
4.3.4 Good Models, Bad Policy, Vice Versa.112
4.3.5 Perceived Reliability. 112
4.3.6 Perceived Validity 113
4.3.7 Summary. 113
5. SUMMARY OF MAJOR FINDINGS 114
6. LIMITATIONS AND ASSUMPTIONS 120
6.1 Neural Network Model. 120
6.2 Statistical Approach. 120
6.3 The Proposed Study. 121
7. RECOMMENDATIONS FOR FURTHER RESEARCH. 122
8. APPENDIX. .125
9. BIBLIOGRAPHY. 147
10. LIST OF FIGURES. 155

1. INTRODUCTION

The purpose of this work is to design and then evaluate a model for comparing the performance of neural networks and statistical approaches in predicting the project profits of an asphalt paving company.

1.1 Background

1.1.1 Company and Problem Features.

<u>Company Features</u>. The company under consideration makes asphalt and paves highways and other areas. It is considered to be one of New Jersey's leading asphalt producing and paving firms.

As a modern construction concern, the firm regularly needs to assess the profitability the projects it undertakes. Its labor cost and its trucking costs are reportedly subject to fluctuation, being tied to its profits (Berry, 1990). The profit margin for a typical paving project is reportedly three to five per cent, although it does vary somewhat. Therefore, even small errors in estimating even one cost component of a project can result in an unprofitable project; ultimately, such losses can pose excessive risk for a firm in the asphalt paving industry.

Like other firms in this and other industries, the company studied normally makes exclusive use of historical financial data in determining the profitability of its projects. A computer and an accounting software program are used to track this data. To bid on a project, a percentage mark-up based on the going market rate is usually used to develop the cost estimate used for the bid. Advanced computerized approaches, such as ones similar to the ones discussed later in this paper, are not yet under consideration by the organization.

The cost components typically included in such project bids are costs for materials, labor, equipment, and trucking; these are normally used in determining the profitability of the project after its completion. The total cost plus the mark-up is typically the approach taken in estimating bids for projects.

Several non-financial factors may have an influence on the profitability of asphalt paving projects, however. These non-financial factors include: the weather, the foreman and/or the crew working on the project, the type of project (highway or non-highway), the size of the project, the number and type of other projects the firm is simultaneously engaged in, and physical characteristics of the job itself (see also Berry, 1990).

A recent review of labor costs of the firm seemed to suggest that profits could be increased very easily if overtime costs were reduced (Berry, 1990). There were also some indications that labor costs could be cut if waiting time for asphalt to arrive at the job site were reduced. The overtime costs seemed more directly related to waiting time at the start of each day's work than to a constraint regarding overall project completion time. Berry has suggested in his study that asphalt can be placed "at rates of up to 300 tons per hour" (Berry, 1990, p. 79).

In this empirical study and evaluation, we make use of a five-stage evaluative cycle developed by Cohen & Howe (1988). The first stage of this cycle discusses the criteria for evaluating research problems. The first stage is presented in the section that immediately follows.

In this section, we utilize the criteria developed by Cohen & Howe for evaluating research problems (Figure 1). The six key questions they ask are addressed in turn below.

Task significance. The task at hand is a significant one because of the low and variable profit margins typically associated with projects in the industry. The problem has been previously defined but its analysis focuses on costs rather than profits; furthermore, analysis of non-financial factors was incomplete. The reformulation of the problem is an improvement because the models under consideration suggest a profitability mark-up based on past experience rather than on "the going rate". A project manager can use these models to improve project profits. Furthermore, in the case of neural network models, non-numeric data can also be considered.

The meaning of this research. In this study, the results of a statistical model and a neural network model are compared. Using quantitative and qualitative measures, the results can be compared. This is a tractable task.

Representative of a class of tasks. The scope of this task has been narrowed to determine the project profitability of an asphalt paving company. This task still exemplifies a research topic, since it is representative of the general class of project profits, regardless of project type.

Abstraction or simplification of interesting aspects. In treating the problem herein, concern for all known aspects of the problem have been included, to the extent that the data was available. It is expected that certain aspects have been omitted, for instance, the size of the crews themselves, the particular persons comprising each crew, and the number of jobs occurring simultaneously on a given crew day. In terms of profits, the actual mark-ups and estimates of the projects under consideration were not available; only historical data is treated herein.

Sub-goals of the research. Several key research tasks are being addressed in this project. First, the task of the development and selection of qualitative and quantitative criteria; second, the task of model selection; third, the task of model development and use; fourth, evaluation of results of each model; fifth, the appropriateness of the criteria used in the evaluation process; sixth, suggestions for future research.

Demonstration of a solution to the task. In this study, a solution to the task of proposing evaluative criteria is demonstrated by the review and discussion of several qualitative and quantitative criteria. The solution to the task of choosing a model based on various criteria is also demonstrated. Since the task of past project profits can be readily measured using statistical models and neural networks, a solution can be demonstrated. Test cases after training or regression analysis, respectively, can be evaluated for their accuracy.

1.2 Review of the Literature

1.2.1 Introduction. In reviewing the literature, this author will attempt to answer a number of questions concerning the application of AI. Specifically, what is the current practical and epistemological impact of artificial intelligence on society? Has artificial intelligence (AI) been demonstrated as a reliable general problem-solver?

When we ask this question, we include neural networks, expert systems, and various hybrids in the group of computer programs called "artificial intelligence". How can the performance of AI models be measured? What criteria, both qualitative and quantitative, have been used in the past (as indicated in published literature)? What questions do potential users of AI-based technology ask in determining whether AI can improve their organization's effectiveness? What case studies to date appear in the academic and popular literature regarding measuring the effectiveness of AI in providing solutions?

The following literature review discusses the development of a model providing evaluative criteria (a metric) for predictive models. Several issues are explored. First, the question of the ability to measure performance of these models at all is addressed. Is it feasible to measure the performance of AI-based or other models? Is it required to measure the performance of such models? Second, a summary of the criteria used in prior published case studies is included. Third, specific quantitative and qualitative criteria for evaluating AI-based models are discussed. Fourth, the questions of would-be users of AI-based technology regarding its reliability in specific task environments are addressed. Fifth, a summary of past published works regarding evaluation of AI-based models in specific case studies is made.

1.2.2 Review of the Literature

<u>1.2.2.1 The feasibility and requirement of measuring the performance of models</u>. We begin with a summary of the discussion within the academic and industrial communities regarding the feasibility and requirement of evaluating AI-based technology.

Incentives for exploring the usefulness and appropriateness of AI-based technology and modeling approaches are numerous. Yet, there are many users and proponents of AI who suggest directly or indirectly that it is neither feasible nor necessary to raise the question of performance evaluation. We will present and discuss some of these views as found in the literature in this section.

The question of evaluation of AI technology occurs within a cautious and optimistic context. Recently, increasing attention is being paid both to this caution and to this optimism. In the case of expert systems, a 1988 conference focused on their reliability generated this comment:

> Expert systems are introduced to solve problems which presumably could not be solved before...but they also create problems themselves in terms of increasing system complexity, a demand for new knowledge representation and knowledge processing methods, a usability which often presupposes significant organisational changes, and possibly a reduced reliability. The question is then whether the benefits of using the expert systems outweigh

> or compensate for the problems that are created by the increased complexity and the added costs. This can in the long run only be resolved if it is possible to define a reasonable metric for these very diverse categories and use that to gather comprehensive empirical data. In order to do so one needs first to provide a clearer understanding of what the salient aspects of expert systems are and how they can be operationalised and measured (Hollnagel, 1989, p. 170).

In contrast, a growing body of literature claims that the need for and the usefulness of any computer-based change within an organization is practically universal. Opinions found in the literature are scarce when the discussion turns to evaluating AI technology and its applications within organizations.

Two well-known researchers in the field of artificial intelligence were cited in a review of their recent book:

> Winograd and Flores are also quite persuasive in their contention that traditional models of decision-making and problem-solving are both self-limiting and potentially dangerous. The current trend in MIS towards designing massive decision-support and executive information systems may well be, at least partly, mis-directed (Barker, 1990, p. 73).

When we compare some of these cautions about the use of AI-based technologies with some of the optimism that has surrounded early promises, we find ourselves in a quandary. These two points of view are representative of what has generally been described in the literature as utopian and anti-utopian genres by Rob Kling (1990) in his social analyses of computing.

Kling cautions us that each point of view is probably incomplete at best.

It is important to note that there are political as well as technical implications inherent in using AI within an organization (see Markus, 1983, and Keen, 1981). Consider that:

> All organizations tend to perpetuate themselves and to keep things in a status quo. You cannot do new things, you cannot do exceptional or unusual things by usual methods, but the tendency of the organization is to keep everything at a beautiful even level where no problems rise above the surface. So when a man comes up with a new idea, and if it is a difficult new idea which necessarily requires the use of new methods, he is ipso facto opposed by the existing organization ("Hearings on", 1959, p. 603).

In his essay "Engineering in an Age of Anxiety: The Search for Inherent Safety", Alvin Weinberg, former director of the Oak Ridge National Laboratory, reflects on modern risks and certainties. "Before the 'age of anxiety,' the public trusted the engineer: devices designed according to code were 'absolutely' safe--or at least did not engender public apprehension" (Weinberg, 1990, p. 50). Although Dr. Weinberg's focus is that of a nuclear scientist, his observations have meaning for those developing or using AI-based technologies. In his view, "...acceptable standards of safety in our media-driven society are very sensitive to the public's perception" (Weinberg, 1990, p. 52). He adds:

> The public's views are, in this age of television, strongly affected by skeptical and articulate elites. These are self-appointed spokesmen for the public interest as they conceive it. Though these elites are often antitechnological, many of them are sufficiently sophisticated to see trade-offs in any assessment of a technology's risk (Weinberg, 1990, p. 58).

If AI-based technologies are to be used appropriately, their performance needs to be reported and demonstrated in the literature. Members of the academic and industrial communities are beginning to explore measures of this performance.

Part of the confusion regarding AI in the public sector echoes deeply epistemological questions within the AI academic community. These questions themselves are not new, according to an article published this fall:

> To offer a retrospective look at the history of thought, at midcentury, philosophers Ludwig Wittgenstein, J. L. Austin, and Edmund Husserl were doing conceptual analysis, not of concepts such as diagnosis and design but of background concepts such as knowledge, belief, and science. To plunge further into the philosophical past, Alfred North Whitehead opined that all of philosophy is but footnotes to Plato. To paraphrase him, much of AI's disputes over models, levels of abstraction, and such are but footnotes to Plato's myth of the divided line in the Republic, where he discusses and related observation, useful belief, and first principles of what we would term domain-type and metadomain models....
>
> To paraphrase Immanuel Kant, tools without continual praxis are empty; praxis without improved tools is blind (di Piazza & Helsabeck, 1990, p. 106).

In a related philosophical dialogue, Winograd and Flores are reputed to have rejected the attribute of decision-making in favor of the attributes of coordination and networking as the cornerstones of organizational management (Barker, 1990, p. 71). The reviewer described Winograd and Flores as one-time supporters, now "critics" of AI. Their "rejection" of the rationalistic perspective (read: expert systems and traditional computer technologies) seems to be "in favor" of hermeneutics, the study of interpretation (which could share similarities with connectionist approaches). While Winograd and Flores appear to have provided extensive support for describing the external world as meaningless without commitment and context, the reviewer notes: "I found this claim to be overstated in light of the evidence offered" (Barker, 1990, p. 72).

Neural network technology has been in existence since the 1950's (Roberts, 1988, p. 41). But Roberts (1988) describes many of the debates about neural networks which he considers pointless, including: the debate over the relevance of the age of the concept of neural networks; the debate over whether neural networks are general purpose machines; the debate over whether neural networks can be simulated on conventional computers; the <u>claims</u> [italics added] as to the efficiency of neural networks; the ill-fitting metaphors as to how neural networks work; the debates over the merits of studying "self-organizing" behavior; and the debates over what neural networks "versus" conventional computers can do (Roberts, 1988, p. 46). Admonishing his readers to "stop arguing over dead issues and get to work" (Roberts, 1988, p. 46), he too points out that very few magazines, mostly journals, have concentrated on negative things to say about neural networks. Roberts' view is that the general discomfort that many people have about neural networks stems from the degree to which neural networks and human brains are _perceived_ to be similar.

Those acknowledging AI "hype, jargon, and inexperience" also note: "The _promise_ [italics added] of the technology is the ability to provide the knowledge worker with answers, explanations, and recommendations in a variety of formats to cope with the tasks and decisions confronting him." (Clark, 1988, p. 80). What is the basis for deciding, in a particular or general case, that Model A's results are as good as or better than Model B's results? What is degree of reliability associated with each result?

In one of the few published discussions on obtaining funding for neural network purchases, Tom Schwartz gives _AI Expert_ readers a tongue-in-cheek quiz "especially prepared for the born-again neural-network researcher struggling to convince a skeptical manager that a neural-network project is worth funding" (Schwartz, 1989, p. 54). He notes sardonically:

> Neural networks are the latest and greatest computer technology on the horizon; they've been getting a lot of coverage in the trade press. This instant media success is attracting skepticism, especially because many publications have been bashing expert systems. Considering the failure of expert systems to achieve the impossible successes so confidently forecast for them, perhaps a heathy [sic] distrust for new technologies is warranted (Schwartz, 1989, p. 54).

William Hill (1989) suggests that AI's actual goal is not the development of models at all but the development of a new medium of representation of human ideas. His analysis of AI technology focuses on AI as a new vehicle for human problem-solving.

> As representations, computations are commitments [italics added] to particular ways of thinking about the world and, thus, are challengeable with respect to the distinctions they make, their decision criteria, and the values they embody [italics added] (Hill, 1989, p. 39).

Hill's view paradoxically aligns him with Heidegger's view of hermeneutics (and the study of interpretation), and simultaneously embraces highly structured approaches to the development and application of AI-based models.

Contrast Hill's view with the that of Hink and Woods (1987). "No matter how uncertain knowledge is represented in an expert system, it is suspect [italics added] if acquired from a human, even a human expert" (Hink & Woods, 1987, p. 41). Note carefully the implications for human performance in the following statement. "If the systems could compensate for human error [italics added] in handling uncertainty, superexpert performance might be achieved" (Hink & Woods, 1987, p. 41).

The article, written "to inform knowledge engineers about what they can expect" (Hink & Woods, 1987, p. 41), attempts to summarize how humans process uncertain information. The authors maintain that humans process uncertain information quite badly, both in the areas of perception and judgement. "The requirements for a system designed to reduce the effects of human factors [italics added] are introduced" (Hink & Woods, 1987, p. 41). The authors of this article appear to suggest that reducing the effects of human factors is ipso facto a system design requirement. "Human behavior does not seem to conform well to the Bayesian model" (Hink & Woods, 1987, p. 45). What is missing in human behavior which accounts for its lack of conformance to the Bayesian model?

The authors explore the concept of calibration.

> A person is considered perfectly calibrated [italics added] when the probability of a correct response is equal to its subjective probability [that is, the level of confidence] (Hink & Woods, 1987, p. 45).

To decrease the amount of human error in the development of expert systems, they suggest that "DEs [domain experts] could be trained to become better calibrated [italics added].... Interestingly, people can be induced to perform optimally" (Hink & Woods, 1987, p. 50).

Concern for performance criteria within the AI community is not new, but it does not appear to be widespread. In the 60's and 70's, some of the work of researchers E. Feigenbaum, M. Minsky, and S. Papert indicated early appreciation of these concerns (E. Feigenbaum, 1977; M. Minsky, 1968; M. Minsky & S. Papert, 1972). More recently, in 1985, a panel session on expert systems at the 1985 International Joint Conference on artificial intelligence was charged with the question:

> How can a knowledge base be subjected to standards of accountability? Who is responsible for what an expert system contains and what it does? (Davis, 1989, p. 61).

The first panelist, Terry Winograd, offered these comments:

> Once systems are actually proposed and built and they are being used, <u>people don't have a sense of what they can count on and what they can't count on</u> [italics added].... The essential issues that need to be raised are not peculiar to expert systems. All of AI has to deal with many of these same things.... The basic issue is that in creating a representation for use in a program...we create an artificial formal domain.... We thereby create a blindness to everything that is not expressible within those structures (Davis, 1989, p. 62).

> I think there's also a more fundamental question about the notion of problem-solving.... It doesn't take into account the process by which the problem itself comes to be formulated. Within the AI literature in general (and certainly within

> expert systems) only lip service has been paid to that issue (Davis, 1989, p. 63).
>
> People who are using an expert system need to understand what its domain really is rather than being enticed by what the domain seems to be about.... Putting an expert system in place of the expert for general use is going to lead to serious problems of misplaced confidence (Davis, 1989, p. 64).

The second panelist, Stuart Dryfus, added the following comments during his presentation:

> We believe that facts, rules, and logic won't get you to full intelligence... But we ought to back off from this obsession with rules, logic, facts, and the like and look at some other approach, perhaps that of the so-called 'new connectionists' (Davis, 1989, p. 64).

Perhaps it is even possible that the "new connectionst" (read: neural network) models can be evaluated using a approach that combines quantitative and qualitative measures.

The popular history of AI seems to be characterized by highs and lows; optimistic claims and broken promises. Such highs and lows seem likely in the absence of evaluative criteria. "The largest complaint seems to be that software developers were myopically focused on their own pet AI issues and did not care whether or not the systems actually performed..." (Pollack, 1988, p. 84).

> But, it is likely that <u>the bottom line</u> [italics added] will dictate the most about future artificial intelligence development. Ian Reid from Data Logic has this prediction, 'I personally feel that the squeeze on profits is such that when [they] feel they can develop successful AI--they will' (Pollack, 1988, p. 85).

It has been suggested that AI technology is a solution (some say, a problem) in search of a market. It would seem that there are many untapped markets for AI-based technology. "If you can make a business case for something, it doesn't matter what technology you use," says Greg Cline (Thurber, 1988, p. 61).

> You don't care if the technology is old, new, flashy or dull. If something meets the business case--either for cost savings or competitive edge--and that something happens to be an expert system, then you'll probably go with it. (Thurber, 1988, p. 61).

Articles with such titles as "Developing Neural-Network Applications" discuss the need for "a development methodology for neural-network projects based on detailed research and empirical results" (Bailey & Thompson, 1990, p. 34). However, this article suggests no criteria independent of the system being evaluated. The focus of this testing and debugging of a neural network is the network itself, not the identification of criteria independent of the network. The article focuses on the processes used to train the network, noting in passing that "predetermining thresholds for accepting the network's responses as significant is important" (Bailey & Thompson, 1990, p. 38). No case studies or examples are included in the article. Their focus is a development methodology, but the wider and more important issue of evaluation criteria is not addressed. Yet they suggest:

> "Following a methodology will also hasten the general acceptance of neural networks as a resource in the advanced computing toolkit, as developers and users begin to understand more fully the capabilities and limitations of the technology" (Bailey & Thompson, 1990, p. 41)

1.2.2.2 Criteria of prior published case studies. In the mid-70's, Charles H. Dym developed a proprietary approach to investment theory (note: not a market forecasting approach) that combined pattern recognition and probability theory.

"So far, both the practical and theoretical results have been far superior to the performance of the Standard & Poor's 500, according to Larry Geisel, president of Intelligent Technology Group (ITG), Pittsburgh" (Laurance, 1988, p. 8). When his model was pilot-tested, Dym successfully compared his results to the Becker rankings, an industry standard. Recent enhancements reportedly have made Dym's new model "several orders of magnitude" better than its predecessor.

Notably, Dym departs from the rest of the market in defining and applying concepts of risk. Furthermore, published details of the performance criteria are not available.

The absence of detailed information about the high performance of any new model may be due to the proprietary nature of the information in a free market economy. The consequences of sharing details of one's success with competitors may be risky. However, the author points out that the data and rules of such systems are not needed in order to develop a priori a comparative model for evaluating their results. This is true whether one is using statistical models, non-computational approaches, neural networks or expert systems in reaching a particular goal.

In the Chase Manhattan Bank, PCLM, a recent AI application that combines statistical and neural network features into one system, is described as "one of the most successful AI applications in the United States.... It addresses a critical success factor in the bank's strategic plan: reducing losses on loans made to public and private corporations" (Marose, 1990, p. 50). Note that this application's success occurs in an environment which is accustomed to quantitative evaluation of its approaches. The degree of success of the system is not addressed. A section of the article sub-titled "System Success" makes no mention of the actual criteria used to evaluate system performance. Marose notes: "Chase tested the system extensively and, having identified many potentially troublesome loans, the bank is now implementing it" (Marose, 1990, p. 52).

Another recent case study provided quantitative testimony to the success of expert systems. Savings to two companies were reported in terms of dollars per year: Dupont, showing a 1,500% return on total cash invested in 50 expert systems; and Digital Equipment Corporation, saving $25 million a year by using applications based on expert systems (Clark, 1988). Even when savings in terms of dollars per year are quoted, a question remains: What is the basis for citing these savings? How can another organization using a similar expert system decide whether its return or its savings is better or worse than Dupont's or DEC's?

When a group of researchers built Cognito, an expert system for installing a particular operating system on a particular computer, they already had experience with building more than 80 other systems. Yet, they reported difficulties in testing, even when intended users and several-non expert computer users were involved in the testing process:

> This experience has reinforced our belief that all expert systems are inadequately tested. <u>No quantitative procedures exist for testing expert systems</u> [italics added]. Most tests merely involve running a few case studies; they do not exhaust all possibilities (Bahill, Harris, & Senn, 1988, p. 42).

Wexelblat too cites problems with testing expert systems. He recounts this case:

> Humans tend to forget that computers are deterministic. A common response to the unexpected behavior of software is to pretend it didn't happen in the hope that it won't happen again. The flaw in the original Space Shuttle control program that delayed the first launch was observed twice during practice runs by technicians who responded by restarting the system. The actual bug had a 1 in 148 chance of appearing at the power-on stage. In both cases, because [pressing] restart fixed the problem, no one followed up. The day of the first launch was one of those 1 in 148 instances, and the launch was aborted (Wexelblat, 1989, p. 75).

Wexelblat cites an expert in the field of artificial intelligence who shares his concern:

> We speak so spectacularly and so readily of computer systems that understand, that see, decide, make judgments, and so on, with ourselves recognizing our own superficiality and immeasurable naivete with respect to these concepts. And, in the process of so speaking, <u>we anesthetize our ability to evaluate the quality of our work and, what is more important, to identify and become conscious of its end use</u> [italics added] (Weizenbaum, 1986, p. iv).

Wexelblat notes the absence of evidence of requirements for expert systems, which he says "tends to be anecdotal (well, we did it this way, and no one complained). Controlled experiments are hard to plan, hard to do, and hard to find in the literature" (Wexelblat, 1989, pp. 77-78).

The most complete report of such an experiment appears to be the work of S. Dutta and S. Shekhar, cited in a recent issue of <u>AI Expert</u> (Caudill, 1990). Caudill summarized the problem, the approach and the results in her article. She notes:

> The researchers wanted to see if a neural network could be used to solve this problem. Furthermore, they also wanted to find out if such a network could perform more accurately than well-known statistical procedures, specifically regression analysis.
>
> For data sets, they collected 47 examples of bond issues randomly and used 30 of them for training; the remaining 17 examples were used as test data. The 30 training set examples included bond issues from all rating categories. After training (or after the regression analysis was performed), the 17 test examples were used to see if the two systems could correctly predict whether each test example was to be rated as an AA bond.
>
> In general, regression analysis was correct approximately 63%-67% of the time in the training set for the six- and 10-element regressions respectively, and the neural networks were correct 80%-92% of the time (Caudill, 1990, p. 42).
>
> As you would expect, the accuracy of both systems was somewhat different when the test examples were used. The regression system achieved a consistent 65% accuracy for both the six- and 10-element cases. The two-layer neural-network systems achieved an accuracy of 82%-88% for six- and 10-element inputs; the three-layer neural network was correct 77% of the time for six-element inputs and 82% of the time with 10-element inputs (Caudill, 1990, p. 43).

Caudill's summary includes a discussion of another quantitative measure of accuracy, the total squared error for each system.

In the same article, Caudill cites work comparing a neural network's results to that of a human, in this case, a mortgage underwriting expert (Collins, E., Ghosh, S., & Scofield, C., 1988, & Reilly, D., Collins, C., Scofield, C., & Ghosh, S., 1990). An analysis of the results is considered, albeit a more qualitative analysis. These results included the observation that "the network was far more consistent in applying the underwriting guidelines than the human underwriter" (Caudill, 1990, p. 45).

In this paper, we are concerned with the development of criteria and their empirical use as a model for comparing two-problem solving approaches, one being AI-based. These last few citings by Caudill are among the few instances found in the literature that approach this goal.

1.2.2.3 Discussion of specific quantitative and qualitative criteria for evaluating AI-based models. Generally, several of the attempts to quantify the results of the use of problem-solving models come from the financial world. Investors historically work in the financial world. The financial world historically makes extensive use of quantitative evaluations; often, financial experts are keenly interested in measuring the results of the approaches they take. For several generations before the development of AI technology, highly developed statistical models were the mainstay of the financial modeling community.

The financial community has varying degrees of faith in artificial intelligence; there is no concensus. For example, Stewart Pahn, manager of $350,000 in assets, views the role of expert systems in his decision-making processes as an augmenting one. "I personally have tried to dovetail, over the years, a subjective approach to technical analysis with purely objective systems, using the systems as a fail-safe against my subjective analysis". (Arend, 1988, p. 24). This same article later acknowledged skepticism among would-be users.

> 'Unfortunately,' says Pahn, 'the investor found that he was not comfortable with a mechanical trading system of any sort. Even though he made money immediately and never had a net loss on his total position of even $500, he decided to close the system out at the end of the first month' (Arend, 1988, p. 101).

Ed Mahler cites large payoffs at E. I. du Pont de Nemours & Company, according to a recent report in Information WEEK. "We get $15 back for every $1 we spend on it" (Fillon, 1989, p. 27). However, the details of this gain are not available.

An expert system called ESES (Expert System Expert System), designed to choose the correct expert system application with 95% certainty, was cited in a recent article. General considerations for choosing an expert systems approach were indicated. "You simply need to evaluate how your proposed application measures up in the areas of domain, human experts, users, and payoff" (Casey, 1989, p. 45), the author notes. In the sub-section entitled "Payoff Characteristics", payoff criteria are described in terms of "time and money at the end". A brief and general discussion of possible related factors ("geographic distribution, availability of expertise, and adequacy of conventional methods", Casey, 1989, p. 47) seemed to focus on the system and the resident expert it will be replacing. Suggestions regarding criteria were not cited, even when an expert system was at work.

When we look towards standard accounting practices such as return on investment in the literature, some interesting comments regarding the use of criteria can be found. In an article entitled "Why R.O.I. Just Won't Work" (1988, p. 17), strategic use of computers is promoted. Several prominent managers in Fortune 500 companies are described as part of "a growing chorus of information systems experts" ("Why R.O.I....", 1988, p. 17). When it comes to evaluating computer systems purchases, R.O.I. should be discarded, according to this group.

Several points in this article made by Michael Vitale, now vice president of The Prudential Insurance Company of America in Roseland, New Jersey, are of particular note. Vitale suggests that R.O.I. never worked in the first place. Second, he suggests that traditional criteria such as R.O.I. have no place in a strategic environment. Traditional criteria assume that "if we don't build a system, things will go along just as they always have." ("Why R.O.I....", 1988, p. 17) In the meantime, your competitor is already gaining market share and competitive edge, Vitale suggests. "Justification for buying strategic systems, in other words, must be matter of conviction, not of accounting [italics added]." ("Why R.O.I....", 1988, p. 17).

The potential user community appears divided on the use of R.O.I. as a measure of the effectiveness of AI. R.O.I. in fact has been used as a measure of effectiveness of the results of a variety of financial models.

A group of manufacturing engineers see the difficulty in using R.O.I. to evaluate expert systems: "Often, the projects that get the green light are the ones that have immediate payback. So, R.O.I. (return on investment) is an important justification factor. The question to answer here is how much is it going to cost to build the system versus how much is it going to save or improve..." (Expert Systems (A Round, 1990, p. 5).

Faced with the difficulty of developing rigorous test criteria, and adding that many of the traditional methods have historically omitted certain qualitative factors, they explain:

> However, companies are finding that many benefits of AI cannot be adequately quantified by the traditional accounting methods. Intangibles, such as improved time to market, increased responsiveness to customer needs and to market changes are difficult to express in today's method of measuring results. (Expert Systems (A Round, 1990, p. 5).

Inherent in this view is an acknowledgement of new benefits which AI ostensibly can provide.

This group of engineers has a dilemma. On one hand, they have been trained to embrace R.O.I., and have used it with apparent success for years. On the other hand, they have high expectations for expert systems and are at a loss for a criteria that points towards its purchase, its use, and its success.

They decide to handle the dilemma in the following way: "As a result, some companies have simply made the decision that AI is a strategically important technology with wide impact on their corporation and they plan to invest in it to help advance them." (<u>Expert Systems (A Round</u>, 1990, p. 5). In fact, so perplexed is this group by the dilemma of criteria that they suggest that: "AI <u>by its very nature</u> [italics added] does not lend itself to exhaustive testing." (<u>Expert Systems (A Round</u>, 1990, p. 6).

Perhaps the test of an AI application is some combination of quantitative and qualitative measures of the results based on some explicit standard.

The market for AI has some development ahead of itself. Fortunately, some of that work has already begun. In perhaps the best work done on the subject to date, evaluation criteria and techniques for empirical AI research are suggested by Cohen and Howe (1988). Not only do they evaluate the problem under consideration for AI application (Figure 1). They also pose a set of questions for evaluating the method of solution under consideration (Figure 2). They develop criteria for evaluating the method of implementation (Figure 3). They evaluate the experimental design (Figure 4). They evaluate the results of experiments (Figure 5). "This is the first step in what should become an ongoing discussion of AI methodology" (Cohen & Howe, 1988, p. 41), they conclude in their discussion. They ask about

> "...negative results. For example, we need to know when methods don't work as expected, when systems perform less well as they become more knowledgeable, when scaling up causes problems. When did you last read an AI paper that said something didn't work?" (Cohen & Howe, 1988, p. 42).

Although this article appeared in a journal two years ago, apparently no one yet has published a case that embraces their evaluative and methodological guidelines for AI. The impetus for their article is clearly not as adversaries but as proponents of AI technology. They explain that their motivation is the "sense that we are wasting opportunities to understand, by empirical and analytic studies, the intelligent artifacts we build at great expense" (Cohen & Howe, 1988, p. 36). The relative absence of such studies in the literature can only further erode future opportunities for applications of AI-based technologies.

1.2.2.4 Questions of would-be users of AI-based technology. Case-study discussions are beginning to be found within the financial and other communities regarding the cautious use and limits of AI-based technology. Two organizations, SMART F$, begun in 1987, and the Computer Professionals for Social Responsibility, appear to represent a growing number of individuals who are concerned about evaluation of these technologies.

In another financial environment, the performance of an expert system reportedly is distorted by the people who use it. Apparently, Paine Webber's rule-based expert system, "gets smarter by virtue of sitting on the block trading desk" (Schmerken, 1988, p. 21). Nevertheless, "the whole issue of whether the expert system is [of] any value to the firm has not been established." (Schmerken, 1988, p. 22).

The concern here is not simply one of attributing more expertise to the system than it is due. The larger concern is that people using the system may begin to ascribe certain learning capabilities to a machine if they are unclear about the limits of its performance. "'The natural progression is that as information technology becomes more versatile,' Diebold told The Journal of Business Strategy in 1988, 'the interplay between an individual and a machine starts to change.'"(Reynolds, G., 1988, p. 68). This progression has implications not only for the usability of the system, but also for managers of any organization using computer technology. Winograd (1988) maintains that such technologies should not be used if the user of them is clearly not able to understand fully the processes of the system that assists him.

"While the software did everything asked of it, the formats of both input and output were virtually incomprehensible to anyone without a computer programming background (Goodwin, 1987, p. 232). The issue of usability, so often the Occam's razor of software success, reappears with double the force, since now, AI-based processes become increasingly illusive. This is particularly true when the intent of the software designer and the manager is to attempt to create a "knowledge inequity" at the boundary of the human-computer interface.

Some researchers have suggested that "experts should be treated by the machine as fallible" (Silverman, 1990, p. 61). Silverman goes on to suggest "a methodology, called cognitive work analysis (CWA), for adapting the generic model knowledge to the specifics of an application" (Silverman, 1990, p. 61). His work acknowledges biases of availability and representativeness which are clearly human attributes and which often make their way into both human and non-human decision-making. Silverman acknowledges the need for understanding domain boundaries and job boundaries. Silverman explores "the paradox that is associated with the <u>difference</u> [italics added] between the way humans form everyday judgments and the way normatively appropriate, scientifically sound strategies would be employed" (Silverman, 1990, p. 63). This comment seems to suggest that there may be job domains for which AI-based technology may never be appropriate. In his work, he strongly urges for verification of the boundaries of a job with the users of the service, whom he calls "the consumers of the knowledge processing service" ("Silverman, 1990, p. 65).

Researcher Nancy Goodwin (1987) has been studying the concept of usability as it relates to human-computer interfaces. Her comments seem to apply to AI-based systems:

> "There <is> a growing body of evidence that shows that providing extensive functionality is not enough: People must understand what the functions do and how to use them." (Goodwin, 1987, p. 231). "...functionality is only one of the factors influencing user acceptance, most of which relate to how the system can be used rather than whether or not a particular function is available" (Goodwin, 1987, p. 230).

Contrast Goodwin's work (also Shneiderman (1980, 1987)) regarding user interface design with more recent commentary in the AI literature:

> The technical capabilities needed to develop effective user interfaces exist, but often no one knows what to do with them. The process of

creating an effective user interface remains very much an art, yet artistic inclinations among software developers remain an undervalued commodity (Potter, 1988, p. 28):

Although the title of this article is "Direct Manipulation Interfaces", its author notes the preponderance of problems stemming from lack of elementary user interface design concepts among AI developers. "If expert systems come into common usage..." he concludes, "...it will be in part because obstacles associated with the user interface have been surmounted" (Potter, 1988, p. 29). Potter offers several specific suggestions to AI interface designers. Care, however, must be taken not to confuse the issue of epistemological truthfulness of the model with the issue of the proper metaphor for the design of the user interface.

> Another motivation for computer use is to help someone do a job better or faster. In these cases, the tasks are generally less structured, and computer use is more <discretionary> (italics mine); whether or not a user considers a computer <necessary> for these jobs depends on how well the computer meets the user's needs. Many office applications, decision support systems, and information retrieval systems fall in this category (Goodwin, 1987, p. 229).

In a review of the impact of expert systems on technology, work, and the organization, Weitz provides his perspective of the current expert systems market:

> Though expert systems are now in the mainstream computer world, they are not yet fully established. While American Express is proud enough of its expert system to have featured it in its last annual report, company officials are

> discomfited by the difficulty they are having in assimilating the new technology. People still regard expert systems as clever, industrious immigrants who wear funny clothes and can't quite be trusted (Weitz, 1990, p. 58).

Weitz examines the impacts of expert systems technology on work and organizations. He pays particular attention to the attributes of current and future markets for expert systems technology. The purpose of needed market research should be:

> To realistically determine the number of organizations with these problems and whether the costs, benefits, and potential strategic advantage afforded by an expert system solution support or discourage the likelihood that expert system technology will be applied (Weitz, 1990, p. 60).

Note that Weitz, who appears concerned about marketing AI, suggests costs, benefits and strategic advantages in determining the use of expert systems in a given application environment.

Wexelblat (1989) also writes about interface requirements for expert systems. He has observed how users of expert systems develop a consistent conceptual model of a system:

> The user forms hypotheses about the system and works within the bounds of the hypotheses. When experience shows different behavior, one of two events occurs. Either users ignore, rationalize, or just don't notice the inconsistency, or they adjust the model perhaps by explicit experimentation (Wexelblat, 1989, p. 75).

"As executives become more familiar with computers, 'machines become more capable of contributing even more to the bottom line'" (Reynolds, 1988, p. 68). In this paper, we attempt to assess the degree of that contribution.

Pollack (1988) cites misgivings that investors have in putting their trust in the results of a machine.

> In the final analysis, no one is sure that the trader will rely on the computer if it is telling him something contrary to his own intuition. This is a key problem for AI systems that use predictive models that correlate intuitively unrelated events and factors (Pollack, 1988, p. 84).

Once standardized criteria for evaluating the results becomes available and used, and the results published, the concerns of the trader can begin to be addressed.

1.2.2.5 Summary of past published works regarding evaluation of AI-based models in specific case studies. Our review of the literature has indicated that quantitative and qualitative demonstrations of the effective use of AI-based technology, and in particular, neural networks, is sparse. If the published literature is an indicator, researchers in AI seem unconcerned with the effectiveness of the systems that are being developed. To ignore the need for established criteria seems to result in a loss of opportunities to win loyal supporters, credibility, and clients.

1.2.3 Summary. The review of the literature reflects a division of opinion regarding the need for evaluative criteria for the performance of AI-based models. Discussions regarding the feasibility of or the requirements for such criteria are few. There are many articles in the literature attesting to successful use of AI-based models; however, the criteria used to draw these conclusions appear to be absent, incomplete, or inconsistent in the examples published.

Where discussions regarding the use of criteria are included, actual case studies demonstrating the application of the criteria to the model under study are not included. Furthermore, there seems to be a general disagreement about the validity of any quantitative or qualitative approach in the first place.

Unless their benefits can be demonstrated, it is unlikely that these new technologies will be adopted.

1.3 Brief Statement of the Problem. In this paper, we propose a model for evaluating the results of profit predictions based on two different approaches: a neural network and a statistical approach. The results are evaluated on several quantitative and qualitative bases.

Figure 1. Criteria for Evaluating Research Problems. From "How Evaluation Guides AI Research" by P. Cohen and A. Howe, 1988. <u>AI Magazine, Winter</u>, p. 36. Copyright 1988 by AI Magazine. Reprinted by permission.

1. Is the task significant? Why?
   (a) If the problem has been previously defined, how is your reformulation an improvement?

2. Is your research likely to meaningfully contribute to the problem? Is the task tractable?

3. As the task becomes specifically defined for your research, is it still representa tive of a class of tasks?

4. Have any interesting aspects been abstracted away or simplified?
   (a) If the problem has been previously defined, have any aspects extant in the earlier definition been abstracted out or simplified?

5. What are the subgoals of the research? What key research tasks will be or have been addressed and solved as part of the project?

6. How do you know when you have successfully demonstrated a solution to the task? Is the task one in which a solution can be demonstrated?

Figure 1. Criteria for Evaluating Research Problems.

Figure 2. Criteria for Evaluating Methods. From "How Evaluation Guides AI Research" by P. Cohen and A. Howe, 1988. AI Magazine, Winter, p. 37.

1. How is the method an improvement over existing technologies?
   (a) Does it account for more situations (input)?
   (b) Does it produce a wider variety of desired behaviors (output)?
   (c) Is the method expected to be more efficient (space, solution time, development time, and so on)?
   (d) Does it hold more promise for further development (for example, because of the introduction of a new paradigm)?
2. Does a recognized metric exist for evaluating the performance of your method (for example, is it normative, cognitively valid)?
3. Does it rely on other methods? (Does it require input in a particular form or preprocessed input? Does it require access to a certain type of knowledge base or routines?)
4. What are the underlying assumptions?
5. What is the scope of the method?
   (a) How extendible is it? Will it easily scale up to a larger knowledge base?
   (b) Does it exactly address the task? Portions of the task? A class of tasks?
   (c) Could it or parts of it be applied to other problems?
   (d) Does it transfer to complicated problems (perhaps knowledge intensive or more or less constrained or with complex interactions)?
6. When it cannot provide a good solution, does it do nothing or does it provide bad solutions or does it provide the best solution given the available resources?
7. How well is the method understood?
   (a) Why does it work?
   (b) Under what circumstances, won't it work?
   (c) Are the limitations of the method inherent or simply not yet addressed?
   (d) Have the design decisions been justified?
8. What is the relationship between the problem and the method? Why does it work for this task?

Figure 2. Criteria for Evaluating Methods.

Figure 3. Criteria for Evaluating Method Implementation. From "How Evaluation Guides AI Research" by P. Cohen and A. Howe, 1988. AI Magazine, Winter, p. 39. Copyright 1988 by AI Magazine. Reprinted by permission.

1. How demonstrative is the program?
   (a) Can we evaluate its external behavior?
   (b) How transparent is it? Can we evaluate its internal behavior?
   (c) Can the class of capabilities necessary for the task be demonstrated by a well-defined set of test cases?
   (d) How many test cases does it demonstrate?
2. Is it specially tuned for a particular example?
3. How well does the program implement the method?
   (a) Can you determine the program's limitations?
   (b) Have parts been left out or kludged? Why and to what effect?
   (c) Has implementation forced a detailed definition or even reevaluation of the method? How was this reevaluation accomplished?
4. Is the program's performance predictable?

Figure 3. Criteria for Evaluating Method Implementation.

Figure 4. Criteria for Evaluating the Experiments' Design. From "How Evaluation Guides AI Research" by P. Cohen and A. Howe, 1988. AI Magazine, Winter, p. 39. Copyright 1988 by AI Magazine. Reprinted by permission.

1. How many examples can be demonstrated?
   (a) Are they qualitatively different?
   (b) Do these examples illustrate all the capabilities that are claimed? Do they illustrate limitations?
   (c) Is the number of examples sufficient to justify the inductive generalizations?
2. Should the program's performance be compared to a standard such as another program, or experts and novices, or its own tuned performance? Should the standard be normative, or cognitive validity, or outcomes either from the real world or from simulations?
3. What are the criteria for good performance? Who defines the criteria?
4. Does the program purport to be general (domain-independent)?
   (a) Can it be tested on several domains?
   (b) Are the domains qualitatively different?
   (c) Do they represent a class of domains?
   (d) Should performance in the initial domain be compared to performance in other domains? (Do you expect that the program is tuned to perform best in domain(s) used for debugging?)
   (e) Is the set of domains sufficient to justify inductive generalization?
5. Is a series of related programs being evaluated?
   (a) Can you determine how differences in the programs are manifested as differences in behavior?
   (b) If the method was implemented differently in each program in the series, how do these differences affect the generalizations?
   (c) Were difficulties encountered in implementing the method in other programs?

Figure 4. Criteria for Evaluating the Experiments' Design.

Figure 5. Criteria for Evaluating What the Experiments Told Us. From "How Evaluation Guides AI Research" by P. Cohen and A. Howe, 1988. AI Magazine, Winter, p. 41.

1. How did program performance compare to its selected standard (for example, other programs, people, normative behavior)?
2. Is the program's performance different from predictions of how the method should perform?
3. How efficient is the program in terms of space and knowledge requirements?
4. Did the program demonstrate good performance?
5. Did you learn what you wanted from the program and experiments?
6. Is it easy for the intended users to understand?
7. Can you define the program's performance limitations?
8. Do you understand why the program works or doesn't work?
   (a) What is the impact of changing the program even slightly?
   (b) Does it perform as expected on examples not used for debugging?
   (c) Can the effect of different control strategies be determined?
   (d) How does the program respond if input is rearranged, noisy, or missing?
   (e) What is the relationship between characteristics of the test problems and performance (either external, or internal if program traces are available?)
   (f) Can the understanding of the program be generalized to the method? To characteristics of the method? To a larger task?

Figure 5. Criteria for Evaluating What the Experiments Told Us.

2. THE NEURAL NETWORK MODEL

2.1 General Characteristics

The profile describing this neural network model combines features obtained from two sources. The first source is a profile developed by D. Brown. This profile has been used in the evaluation of software, as part of a graduate level expert systems course. "The profile was developed with the help of sources such as Gevarter (1982) and Hayes-Roth, Waterman, and Lenat (1983)." (Brown, 1987, p. 36). This profile does include some overlapping items; however, it appears to be comprehensive.

The second source is the work of Cohen & Howe (1988). The second step of their suggested evaluative framework suggests criteria for evaluating methods (Figure 2).

Information from these two sources was combined and modified, the resulting profile being used as a framework for describing the general characteristics of the neural network model under consideration.

2.1.1 Domain. General purpose, a wide variety of tasks.

2.1.2 Main general function. A model that simulates a biological neural network. Like biological neural networks, through training, it finds patterns in data for a particular result.

2.1.3 System name. BrainMaker.

2.1.4 Dates. BrainMaker was first copyrighted in 1988.

2.1.5 Researchers. Mark Lawrence, Al Petterson, Jon Hartzberg.

2.1.6 Location. Sierra Madre, California, 91024.

2.1.7 Language. C.

2.1.8 Machine. Runs on an IBM PC or compatible or PS/2 or compatible.

2.1.9 Brief summary. BrainMaker is an all-purpose system for developing neural networks. Symbolic and numeric data can be used. Users make choices from a menu to manage files, to define networks, and to train and to test networks. The BrainMaker software includes NetMaker, software that assists in the neural network development process.

2.1.10 Related systems. None.

2.1.11 Characterizations of givens. The system supports several types of neurons. The system includes options for displaying inputs and outputs so they can be easily seen. Data from most accounting spreadsheet type software programs can be read as input data.

Opportunities to slow the learning rate, change the learning tolerances, and the number of hidden neurons are included. Opportunities to add noise to the data, to specify diagonal or 8-way symmetry for the input facts, to specify blurs, to graph data, to write macros, to specify weighted matrices are included.

2.1.12 Characterization of output. Output can be numeric or symbolic data.

2.1.13 Characterization of data. So long as data is not directly contradictory, BrainMaker is reputed to find the pattern in the data, provided enough facts are used to train the network. BrainMaker can handle missing values in the data.

2.1.14 Generic tasks. The software accepts any numeric or symbolic data as inputs and outputs, and finds patterns in the data. Many generic tasks involving data analysis are candidates for BrainMaker application. Sample neural networks included with BrainMaker software recognize optical characters, predict exchange rates, convert text to speech, recognize fruit based on shape and color, categorize and process images, and play Tic-Tac-Toe.

2.1.15 Theoretical commitment and reality. A modified back propagation approach is the theoretical basis for BrainMaker's learning scheme. The documentation is written in a way that does not claim exact similarities between how BrainMaker learns and how humans learn. The reference book accompanying BrainMaker discusses such topics as biological neural networks and whether machines can "learn". No specific theoretical claims are made, except that neural networks <u>seem</u> to mimic associative reasoning. Therefore, there may be "psychological validity" to the neural network approach of problem-solving generally. BrainMaker is not a simulator of a particular result, at least not as the term "simulator" is typically used.

2.1.16 <u>Completeness</u>. The system has been fully implemented. All of the domain has been included.

2.1.17 <u>Use and performance</u>. BrainMaker has been used with real users outside the original development environment. It is possible to measure the how well the network learned by presenting test cases to the trained network and by comparing the predicted output with the actual output. Such a measure is a test for internal validity. There are no performance measures for external validity available, except as developed on a case-by-case basis.

2.1.18 <u>Phases</u>. BrainMaker activities are organized into distinct phases. In the first step, the user of the system prepares the data for acceptance by BrainMaker. Once the data is presented, BrainMaker randomizes the connection strengths to facilitate its learning process, and sets aside every tenth fact for its test file. Next, BrainMaker compares pairs of information, input and output, adjusting internal connection strengths, and repeating the entire process for each new fact. The training process continues in this iterative fashion until it is completed.

2.1.19 Subfunctions. BrainMaker can evaluate information or associate information. Evaluating information means the ability to handle situations that involve making a decision. Associating information means the ability to recognize a pattern in information. It is also possible to create a network with BrainMaker that has both evaluative and associative characteristics.

2.1.20 Use of simulation or analysis. The system does not use any numeric simulation or analysis.

2.1.21 System/control implementation architecture. BrainMaker departs from normal serial computer architecture. Neural networks fit better on parallel machines than serial machines. BrainMaker permits several "hidden layers" between the input layer and the output layer. Learning parameters include the noise bandwidth, the training tolerance, the testing tolerance, the backpropagation learning rate, and the backpropagation smoothing factor. BrainMaker uses the backpropagation learning algorithm.

2.1.22 Characterization of structure knowledge. BrainMaker does not group knowledge except for categorization into numeric or symbolic data. At the user's request, BrainMaker will represent either as "thermometer" type data.

2.1.23 Characterization of process knowledge. Intermediate values of partially learned network have very limited usefulness.

2.1.24 Deep or surface. There is theoretical evidence suggests that BrainMaker's approach to learning is simultaneously deep and surface.

2.1.25 Search space. To the extent that this concept applies, BrainMaker's "search space" is all the input data provided by the user in developing the network. The limits of the standard software include maximums of 512 neurons per layer, 32,767 connections per layer, 8 layers, and 4096 characters in an input line. Standard version permits either numeric or symbolic data but not both in the same network definition file.

2.1.26 Space traversal. Not applicable.

2.1.27 Search control strategy. Not applicable.

2.1.28 Standard search strategies. Not applicable.

2.1.29 Subproblems. The evaluation of partial solutions is not possible.

2.1.30 Search control representation. Not applicable.

2.1.31 Search control strength. Not applicable. Since BrainMaker uses a learning algorithm that does not use "searches" per se, it does not make sense to talk about the weakness or strength of the search based on the degree of dependence on a given domain.

2.1.32 Failure method. BrainMaker is likely to not learn when given diametrically contradictory facts, for example: A always implies B, and A never implies B. BrainMaker can find patterns or reach conclusions even if the conclusion itself is very weak.

2.1.33 Uncertainty. As represented by pieces of missing data, BrainMaker can learn in spite of this uncertainty. It is better to give BrainMaker more data than it may need; BrainMaker can ignore redundant or inconsistent or inconsequential data as it learns. BrainMaker makes use of the data it has; it learns better and faster with more data rather than less.

2.1.34 Management of uncertainty. The backpropagation learning algorithm manages missing or inconsistent data. BrainMaker does not use probabilities, scoring values, a fixed range of certainty values, or data not provided to it when learning.

2.1.35 Management of time. BrainMaker takes more time to learn depending on how noisy the data is to start with and how accurate the user specifies the results to be (by setting a learning tolerance factor).

2.1.36 Knowledge representation method. Numeric or symbolic data, optional conversion to "thermometer" display.

2.1.38 Knowledge representation generality. Not applicable.

2.1.39 Knowledge structuring. BrainMaker is based on a neural network. Hence, correspondence between system, domain, and problem-solving method does not apply.

2.1.40 Alternative representations. Not applicable.

2.1.42 Alternative solution methods. Not applicable.

2.1.43 Optimization and multiple results. Given time to learn, BrainMaker seems to produce the best answer it can. If the data is presented in a slightly different order, it appears that there could be very slight variations in its "best" answer.

2.1.44 Interaction. An interesting feature of BrainMaker is its use of the thermometer display of information. Its menus are easy to use and powerful too.

2.1.45 Data collection, format and acquisition. BrainMaker permits the attachment of additional fact files to a trained network; training to include the new facts can continue. Data is provided using accounting software, or the editor or data manipulator that accompanies BrainMaker. Data is typically alphanumeric or special character data, typically in columns with a one word label at the top of each. Since there is no expert, there is no one from whom BrainMaker acquires "knowledge" per se. Validation of "knowledge" internally in accomplished through the backpropagation algorithm.

2.1.46 Learning. BrainMaker learns from its own performance in that its algorithm, a back-propagation learning algorithm, feeds an error signal back through the network. In this way, it speeds the learning process by learning from itself. However, this feature is part of BrainMaker's internal learning structure. BrainMaker does "learn" from its own cumulative performance based on the facts it is given.

2.1.49 Explanation. BrainMaker has limited ability to explain where its result came from. A professional version of BrainMaker can identify which data is more responsible than other data in contributing to the output, a kind of weighting.

2.1.50 Strengths. BrainMaker's general purpose and connectionist attributes make it ideally suited for financial and other applications. Recent versions include NetMaker, which makes the current version 2.4 much easier to use the version available even last year. Numerous examples included with the software and documentation provide a rich environment for understanding how neural networks work. Especially helpful are the theoretical chapters. The network seems to learn quickly, and conveniently posts its run time in the upper right hand corner of the display for the user.

User support by the staff is available via telephone. Everyone providing user support has been most helpful and most willing to answer questions.

2.1.51 Weaknesses. BrainMaker's standard version does not permit the mixing of numeric and symbolic data in the same fact file. This is a disappointment. Its much improved introductory book could benefit from yet another round of improvements; its style is often stilted. The actual automatic saving of every 10th case (for testing purposes later) is described in the user manual as being 10% of the cases. This description leaves the user in a quandary, not knowing which 10% were selected.

Continuing with the second step of Cohen and Howe's criteria (see Figure 2), we examine the use of this software as a method for solving the problem of predicting project profits.

How this approach is an improvement over existing methods. BrainMaker could be used by the company to analyze past project data in assisting managers pricing current bids. The software itself could have other additional uses within the organization. The manager using the software can choose to train the network within certain tolerances, using the software to determine the relative accuracy of a particular profit estimate. Existing approaches such as certain statistical methods require an understanding of the statistical methods; it is possible for someone to use BrainMaker without understanding its learning algorithms or the mathematics on which they are based.

BrainMaker, once trained, takes usually only a few seconds to develop a solution to a given test fact. Development time is largely confined to data manipulation (in the style of accounting software packages), and training time (in many cases taking less than one day). BrainMaker holds promise for additional development, as its learning algorithms can be used for a variety of kinds of data and problems.

Evaluating the performance of the method. There are no industry-specific or software-specific metrics currently recognized for evaluating BrainMaker in this application area.

Reliance on other methods. Brainmaker does require input to be in a particular form, for example, in labeled columns of data. Additionally, certain restrictions as to the type of data (either numeric or symbolic) apply. There are no specific constraints regarding the type of knowledge that may be represented.

Underlying assumptions. This section deals with what aspects of the research tasks have been omitted from this study. These aspects are discussed in Chapter 6.

Scope of the method. The scope of this method is extendible. The approach taken in developing this BrainMaker model can be scaled up to a larger input file. The method addresses the need of managers to understand how to develop bids and to choose projects that will result in profits for the company. While the method focuses on each day's profits and not the entire project's profits, it is true that the profits of each day for that project, when summed, indeed represent that project's entire profits. By examining each day's profits, daily fluctuations can be more easily examined and analyzed.

Tasks that involve daily work on a project are represented by the task under study. Parts of these tasks could be applied to other problems, such as other kinds of construction, consulting, or engineering projects. There are also some indications that this method can be used in measuring marketing inputs (advertising) and outputs (sales).

This method also can be transferred to more complicated problems, ones involving even more input variables and output variables, and more seemingly unrelated inputs.

When BrainMaker cannot provide a good solution, it may provide a bad solution, or it may provide no solution at all. The researcher chooses the learning tolerances and the testing tolerances. If the learning tolerances are set too high (so that the results are unacceptable), BrainMaker will provide a solution that is not a good solution. If the learning tolerances are set too low, BrainMaker may not be able to provide a solution at all. Given the tolerances set by the researcher, BrainMaker gives the best solution given the available data and constraints.

<u>How well the method is understood.</u> This aspect of the method is treated in Section 2.2, Theoretical Considerations. If the inputs and format of the data are internally contradictory or syntactically incorrect, BrainMaker will not be able to solve the problem it is given. The limitations of the method are discussed in Section 6.

<u>Relationship between the problem and the method.</u> The problem is a complex, dynamic one, and the parameters surrounding project profits for this asphalt paving company are not well understood. For these reasons, the use of the neural network as a method for evaluating project profits seems to be an appropriate choice.

2.2 Theoretical Considerations.

We begin by suggesting the context within which the theoretical considerations underpinning this study can be viewed:

> It is important to note at the outset that no empirical test can prove that a theory is true. A theory may be shown to be in good agreement with the empirical evidence, but since it is not possible to test all of the infinitely many alternative theories, some of which may agree equally well with the data, the failure of a particular theory to be rejected is far from conclusive proof that it is true. It is for this reason that it is especially important to develop tests which are not easily satisfied. (Bass, M. & Parsons, L., 1969, p. 104).

Theoretical considerations of AI-based models, such as the mathematical characteristics, the temporal issues, and the issues of learning, are important. Nevertheless, the detailed treatment they deserve is beyond the immediate scope of the current study. The reader is referred to several excellent sources regarding the development of neural networks, in particular, the works of S. Grossberg (1982, 1988); J. Hopfield (1986); and D. Rumelhart, G. Hinton, and J. McClelland (1987).

In a recent article discussing the theoretical considerations of neural networks, the following explanation of the learning algorithm of the neural network model used in this study was provided:

> Backpropagation is the gradient descent system that tries to minimize the mean squared error of the system by moving down the gradient of the error curve. In a simple system, the error curve is a smooth paraboloid, or bowl-shaped curve. In this case, the network is guaranteed eventually to get to the bottom of the bowl; no bumps or detours exist to trap the network. (Caudill, 1991, p. 58)
>
> In real life, however, the network is not a simple one-dimensional system, and the error curve is not a smooth bowl-shaped curve that can have all kinds of bumps, valleys, and hills the network must negotiate before finding its lowest point (the minimum mean squared error position). As a result, training the network to find that lowest point becomes more of a challenge than you would expect. (Caudill, 1991, p. 58.)

For a detailed treatment of the theoretical considerations, the reader is referred to the sources listed above.

2.3 The Development of This Profit Model. Data for this model was obtained from reports of the asphalt paving company. The raw data can be found in the Appendix of this paper. Raw data in this study consists of data for each of 130 crew days. A crew day is a day on which a particular project was worked on. Note that there can be two crew days for one calendar day; two distinct work crews working at two distinct work sites on the same day.

Raw data includes several variables. Based on discussion and research regarding measures of productivity, two of these variables were selected as output variables (dependent variables): gross profit and gross profit per ton. The remaining variables were selected as input variables (independent variables). These remaining variables included some data that was constant regardless of the crew day selected; these variables were eliminated from the model.

The remaining variables fell into three categories: financial (e.g., total cost of asphalt), non-financial but numeric (e.g., tons of asphalt), and non-numeric (e.g., the foreman's evaluation of the weather conditions).

The original experimental design included numeric and non-numeric data, to illustrate the capabilities of neural networks to process such data analysis; when it was determined that this edition of the software could support use of numeric or non-numeric data, but not both, the non-numeric data was eliminated from the model as well.

Data was originally obtained as a Lotus(C) data file. Data was edited using Lotus and VP-Planner Plus(C). The totals at the bottom of the columns were deleted, as they were not applicable to this study. Due in part to file size constraints, and in an effort to eliminate as much redundancy within the data set as possible, all columns of data that were clearly redundant (sums or products of data represented in another column) at face value were eliminated. The data file was modified to eliminate blank spaces between columns in an effort to save additional file space. The resulting file consisted of 130 cases and 29 variables (including the two output variables described above). The labels at the beginning of each column were not deleted, as BrainMaker would need these column headings for later identification and display purposes. The file was printed as an ASCII text file with a .prn extension; this procedure insured that the format of the file would be compatible with BrainMaker.

Using the NetMaker program of BrainMaker, the data was checked for completeness. Blanks in several of the non-numeric columns were replaced by the underscore character ("_"). Data file was checked to insure that each column had complete information, that there was a space between each piece of information in each row, and that there were no blank lines in the file.

Each column was labeled to indicate which variables were to be ignored, which variables were input variables, and which variables were output variables. When it became clear that only one type of variable (either numeric or non-numeric, but not both) was permitted, non-numeric variables were eliminated. After all the columns were identified, and the file re-named, every tenth fact (row) was set aside by NetMaker and placed in a special test file for later use. Thirteen test facts were set aside.

Using BrainMaker's main program and standard parameters (see Figure 9 for a list of these parameters and their values), the neural network was run. Twenty-seven input variables were displayed; two output variables were displayed. See Figures 5, 6, 7, and 8 for selected training statistics of the trained network. The network required 2-3/4 hours to be trained within the standard parameters.

During the training phase, BrainMaker reported 118 good facts and 0 bad facts, with no compensation for any errors, after 2-3/4 hours of training. The test facts were then submitted to the trained network. (See Figures 10 through 22 for BrainMaker's screen displays of each test fact.)

As suggested by the BrainMaker developers, a tolerance during training of .1 was set; this value was described as standard. A looser tolerance of .4 was used during testing; this was the default value for this variable during the testing phase.

Continuing with the evaluative framework of Cohen and Howe, we now evaluate the method of implementing this model (Figure 3).

<u>How the program demonstrates the method.</u> The results of the BrainMaker program are expressed in terms of the output variables, Gross Profits and Gross Profits/Ton for each crew day tested. These outputs can be evaluated externally by comparing these predicted values with the actual values, using several methods (we chose RMS). The internal behavior of the

network is not particularly transparent and does not lend itself to easy evaluation. Given a well-defined set of test cases and appropriate learning parameters, it is possible for BrainMaker to demonstrate its predictive capabilities. Thirteen test cases were used.

Special tuning. BrainMaker was first trained and tested in this study using standard learning parameters. Subsequent training and testing involved changes in these standard parameters.

Implementation of the method. BrainMaker seems willing to accommodate changes in a variety of its learning and display parameters. Because this methodology includes the caveat that adjustments to the learning parameters may be appropriate, these adjustments can also be considered iterative steps in the implementation. The evaluation of the results, as demonstrated by the calculation of RMS, can indicate additional training of the network using non-standard parameters.

Predictability of performance. The performance of BrainMaker is predictable, in that looser learning tolerances result in a wider range of acceptable outputs. Given a new set of training data, the performance of a network using standard tolerances is usually difficult to predict.

2.4 Summary of Major Findings. In processing the training examples, the neural network eventually learned the facts it was given; the training tolerance was set at 10%. The 10% tolerance implies a maximum acceptable error of 10% for any given fact.

Since the problem environment is dynamic rather than stochastic, we use the Root Mean Square (RMS) as a measure of the degree of accuracy. RMS is used in areas that exhibit dynamic behavior, such as circuit theory and kinetic energy of gases. To calculate RMS, the differences between each actual and forecasted value are squared for each case; the squares are summed; that sum is divided by the number of cases. The square root of the resulting quotient is the Root Mean Square. In using the RMS, we are measuring the deviation of the predicted costs from the actual costs for each crew day. The mean squared root of the neural network was 3304.488 for Gross Profits, and 6.16 for Gross Profits/Ton.

Given the high RMS result, an attempt to re-train the network at a smaller learning tolerance was made. During this attempt, a learning tolerance of .02 was used. This attempt to train the network at a smaller learning tolerance abandoned after over ten hours of training. Since the network took more than ten hours to learn, training was stopped before completion. No testing of examples took place following this attempt.

2.5 Discussion

When the learning tolerances were set relatively high, the network model seemed to learn within a reasonable time. However, the Root Mean Square for the predicted values for Gross Profits seemed high compared to the Root Mean Square for the predicted values for Gross Profits/Ton.

One possible explanation for the relative accuracy in predicting Gross Profits per Ton is the fact that the variable Tons of Asphalt was included as an input variable. Since BrainMaker had an opportunity to take this input variable into account during the training phase, the variable may have effectively acted as a scaling factor, thereby reducing the RMS.

Results for the variable Gross Profits appeared unreliable at first glance, due to the overall magnitude of the RMS. In addition, the two output variables seemed to behave in an inconsistent manner; where positive Gross Profits were predicted for a particular test case, negative Gross Profits per Ton were reported, and vice versa, for certain test facts.

BrainMaker's strengths and best uses are not in performing numeric calculations. The results obtained in the tests for the Gross Profits variable appear to be consistent with this view. Considering the low number of facts used, and the specified learning tolerances, the results obtained for both output variables are both reasonable and expected.

When the learning tolerances were set at a lower value, the neural network model took longer to learn, as expected. The observation of the training of the network at additional trial tolerances indicated difficulty learning several specific facts. These facts were double-checked for their reasonableness and for their accuracy. The values used in the neural network corresponded to those found in the raw data. It is possible that the several facts posing learning difficulties may have represented contradictory information; this would account for the lack of convergence of the network in spite of its relatively long learning cycle.

Figure 6. Number of "Bad" Matches vs. Number of Runs:
Range: 1 to 989

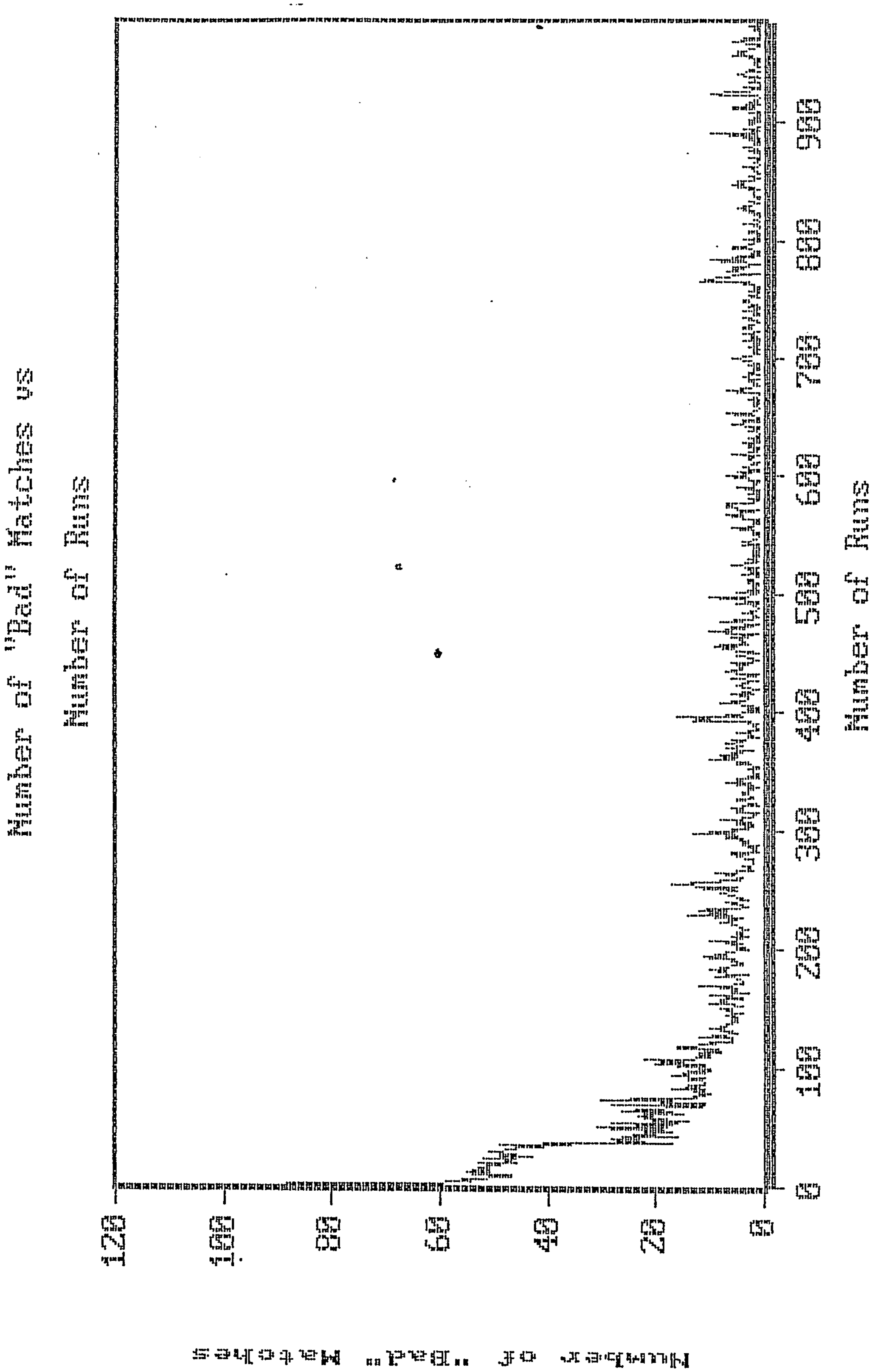


Figure 7. Number of "Bad" Matches vs. Number of Runs:
Range: 1 to 100

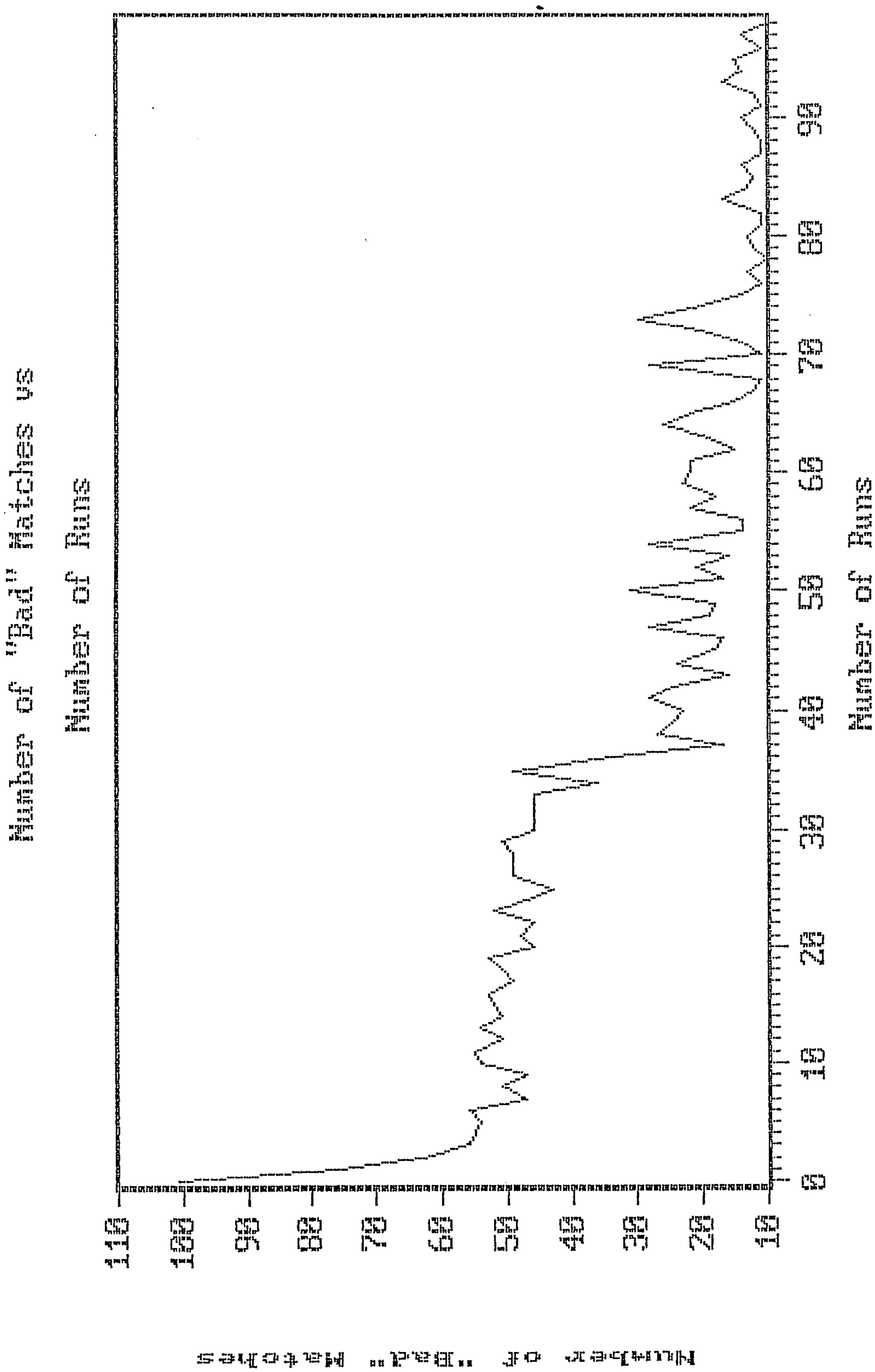
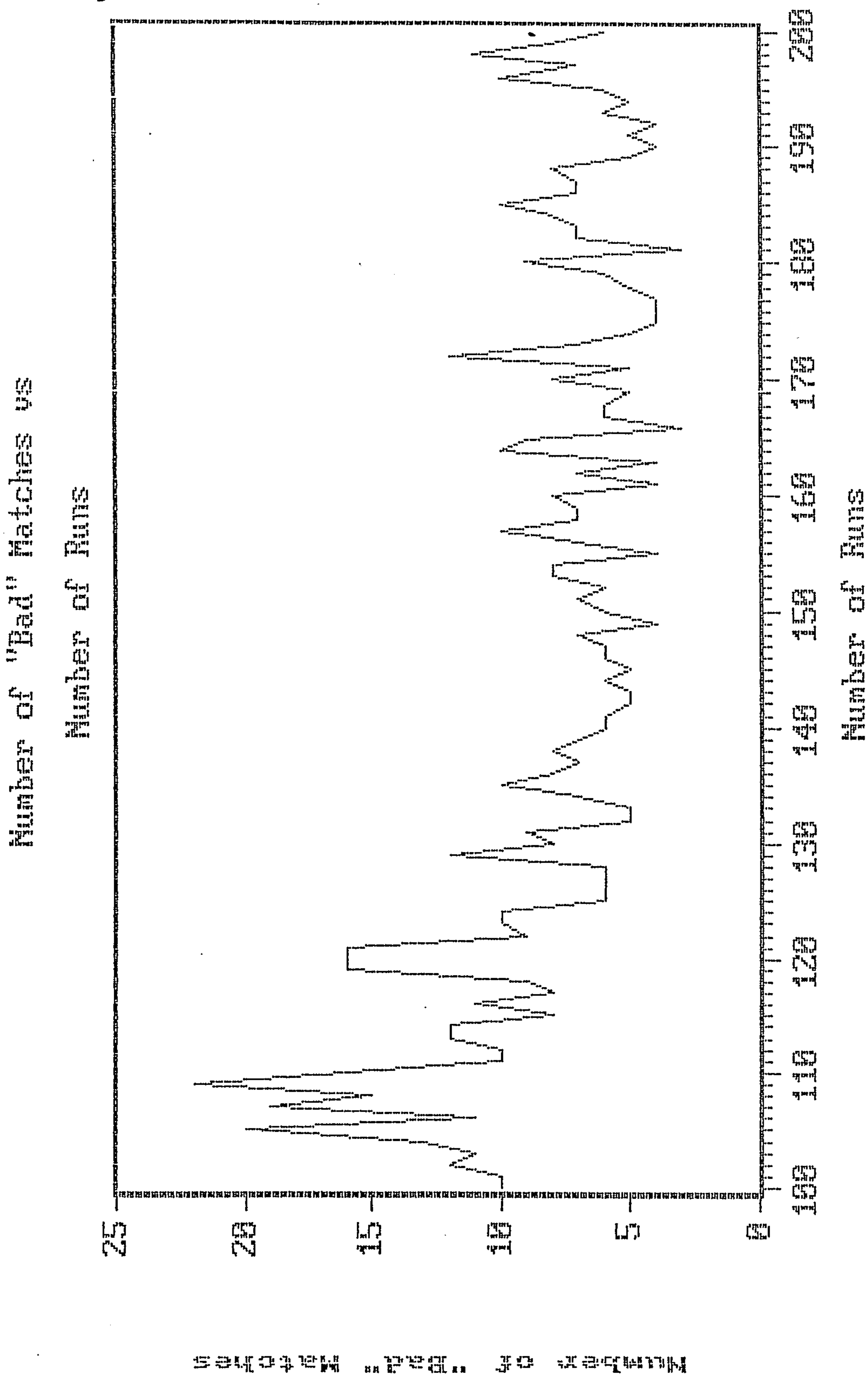


Figure 8. Number of "Bad" Matches vs. Number of Runs:
Range: 101 to 200



```
5:57  BrainMaker v2.2 Copyright(C)1990 California Scientific Software   0:00:00
 System  File  Run  Parameters  Options  Display  Print
Waiting  Files: datextr2.net  datextr2.prn    Learn Rate: 1.000 Tolerance: .100
Fact: 0    Total: 116466  Bad: 0    Last: 0    Good: 0    Last: 118  Run: 987
 mi         toa        tca           gpft
                               Out:
 tctack     lreghr     tclrh     Ptn:
                                     gpft/t
 loth       tcloth     tlhrs

 tclalhr    opregh      Learning Parameters
                                  Noise Bandwidth: .100
 opoth      tcopoth           Training Tolerance: .100
                               Testing Tolerance: .400
 tcopah     tlrh           Backprop Learning Rate: 1.000
                        Backprop Smoothing Factor: .900
 tlabhr     tclab

 tcequ      ttrhr      tctru

 tvc        toh        trev
```

Figure 9. BrainMaker Screen Display: Learning Parameters

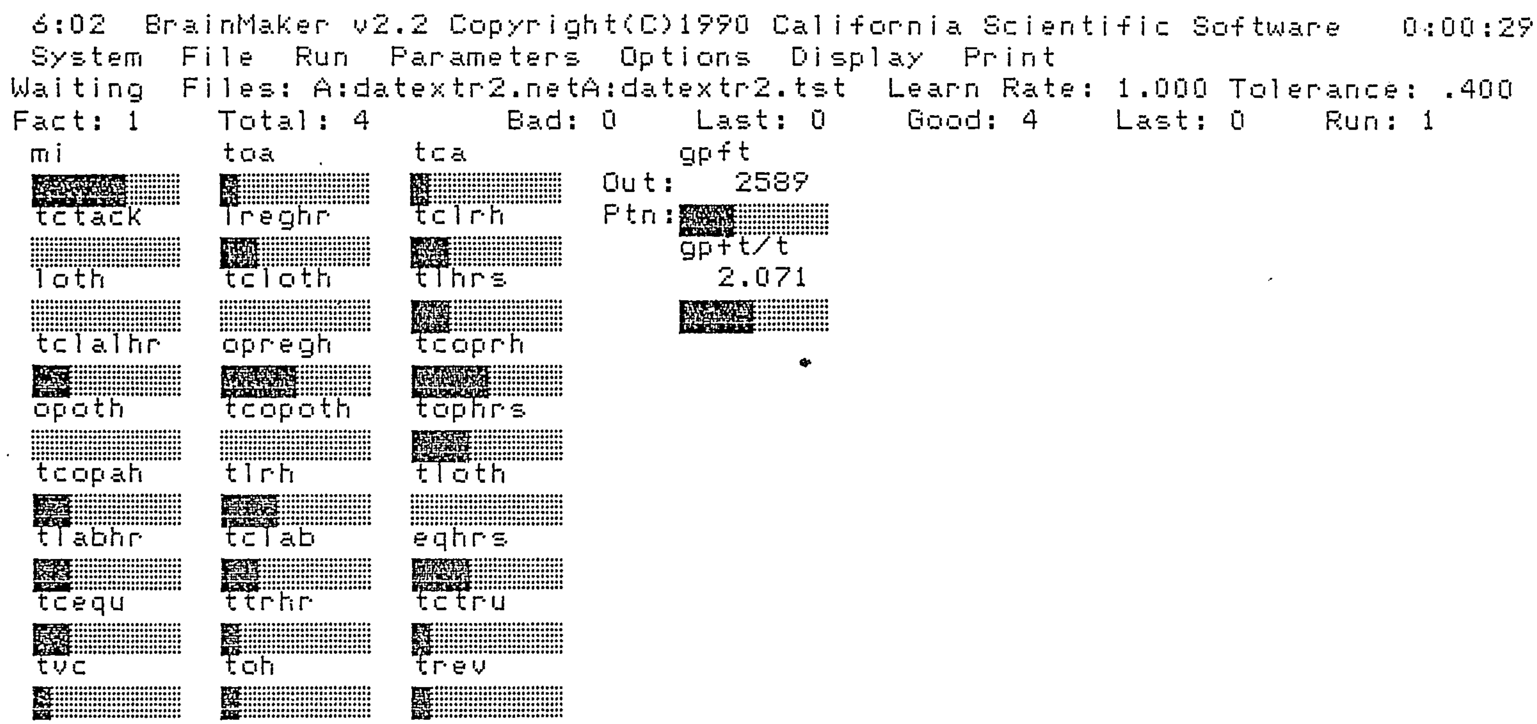


Figure 10. BrainMaker Screen Display: Test Fact 1

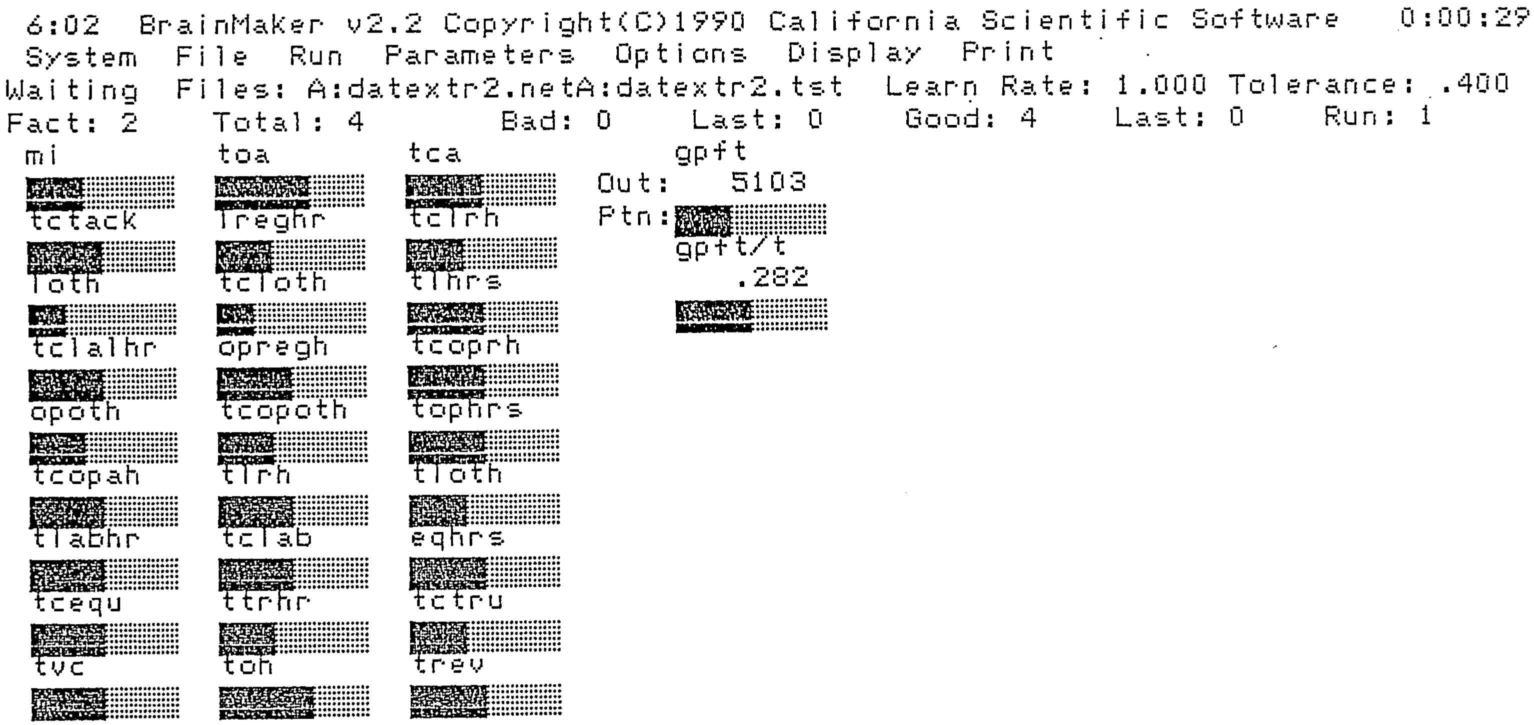


Figure 11. BrainMaker Screen Display: Test Fact 2

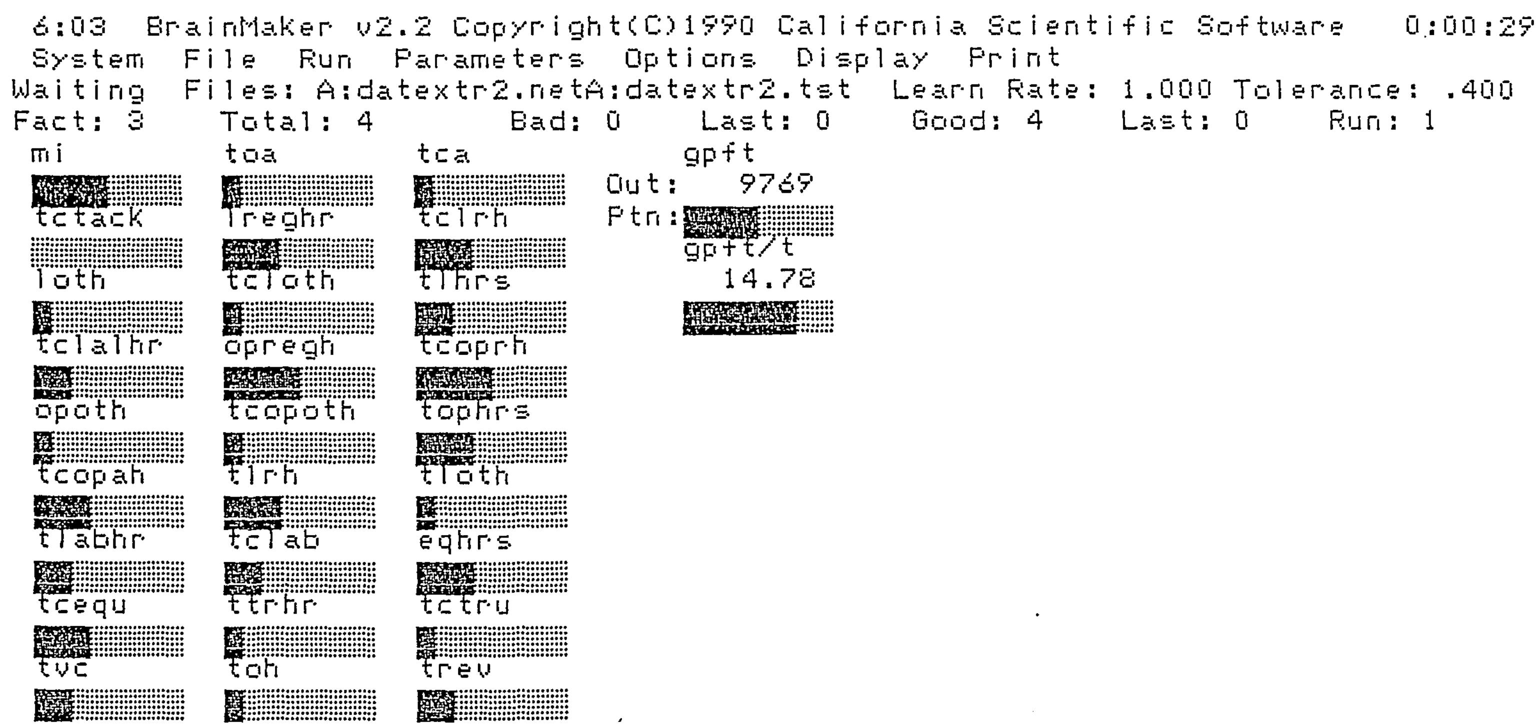


Figure 12. BrainMaker Screen Display: Test Fact 3

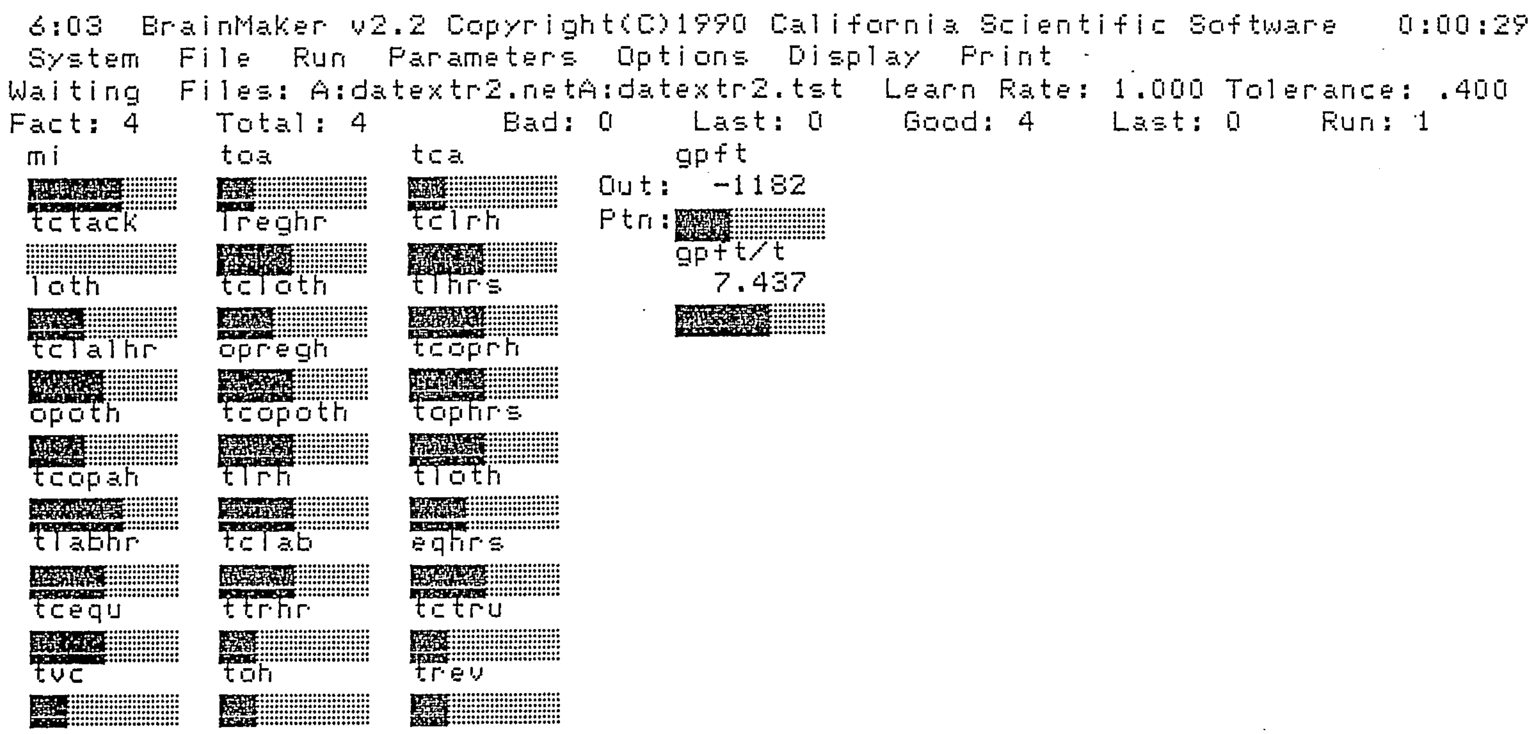


Figure 13. BrainMaker Screen Display: Test Fact 4

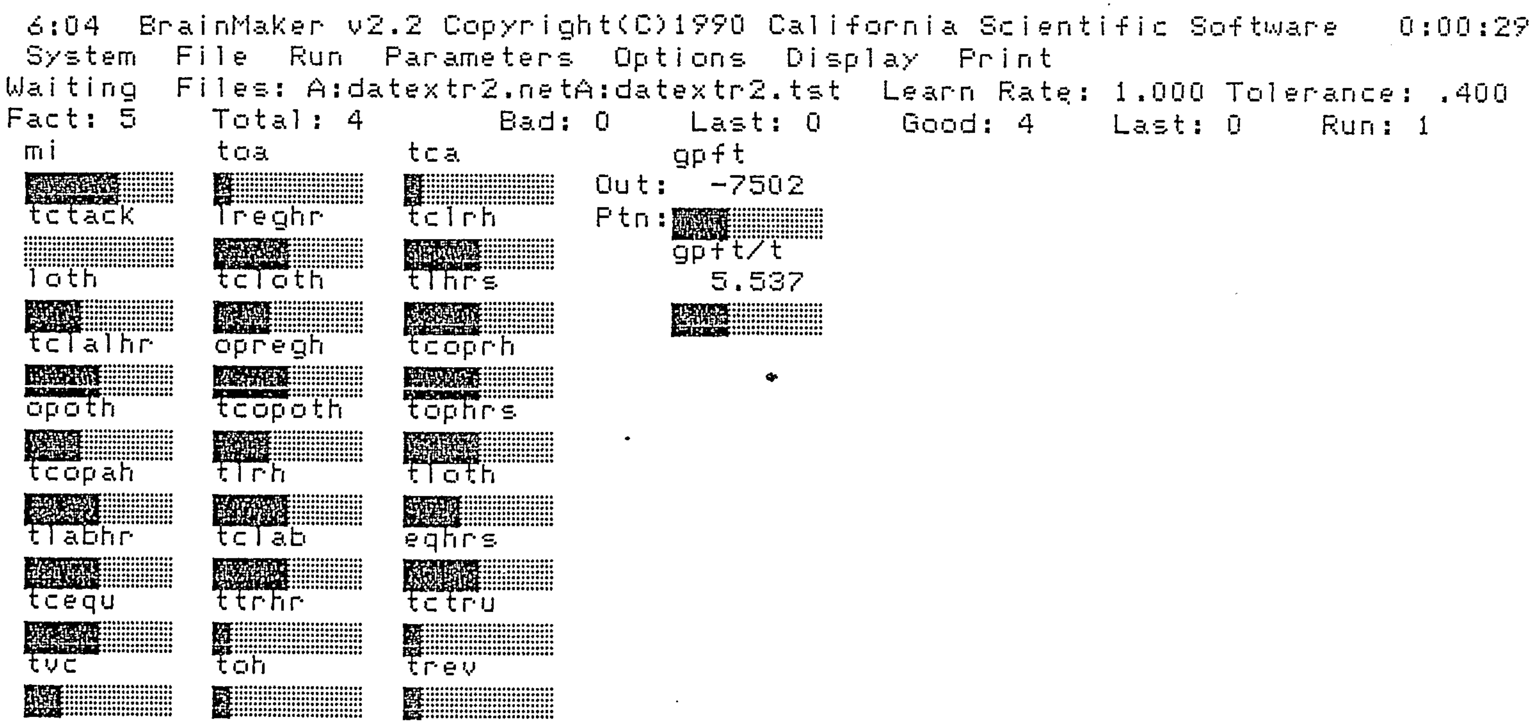


Figure 14. BrainMaker Screen Display: Test Fact 5

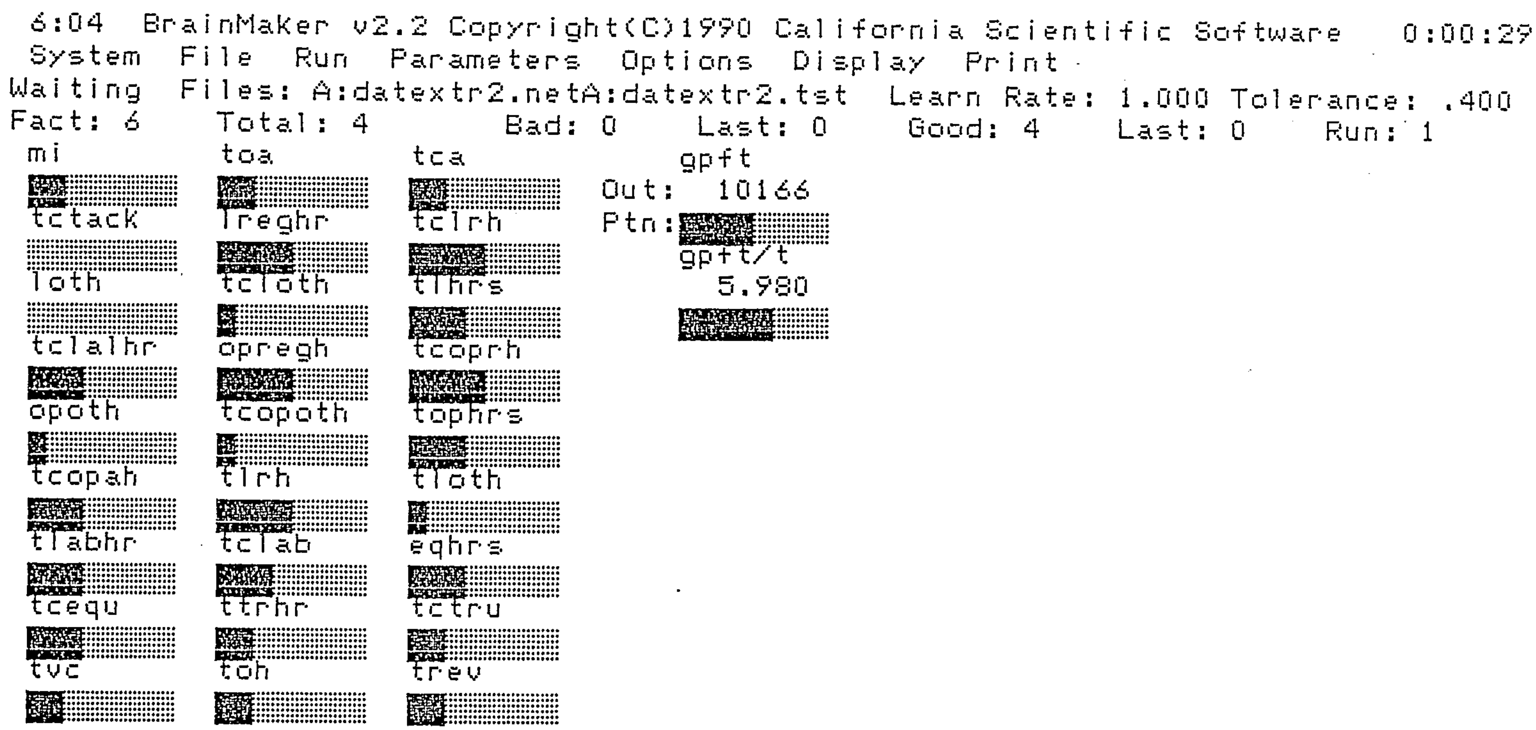


Figure 15. BrainMaker Screen Display: Test Fact 6

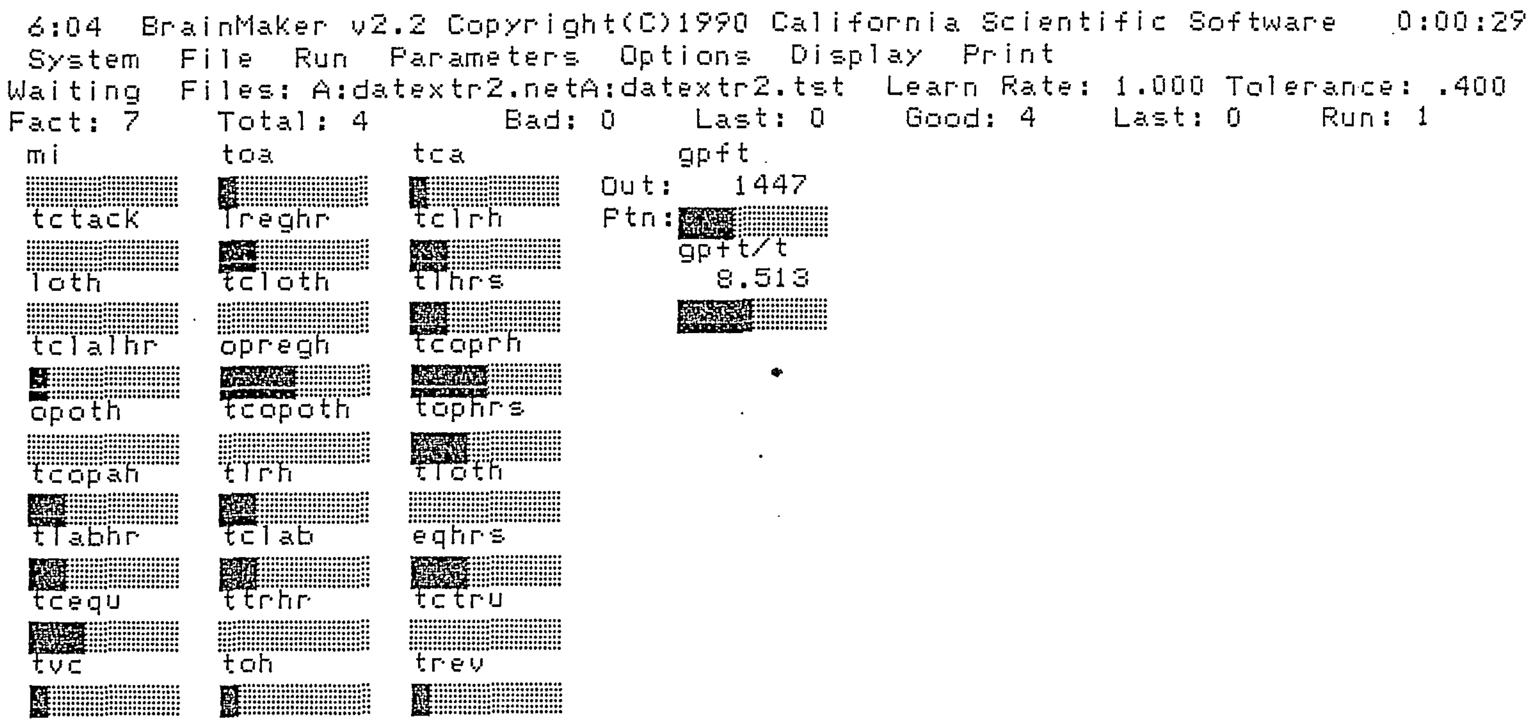


Figure 16. BrainMaker Screen Display: Test Fact 7

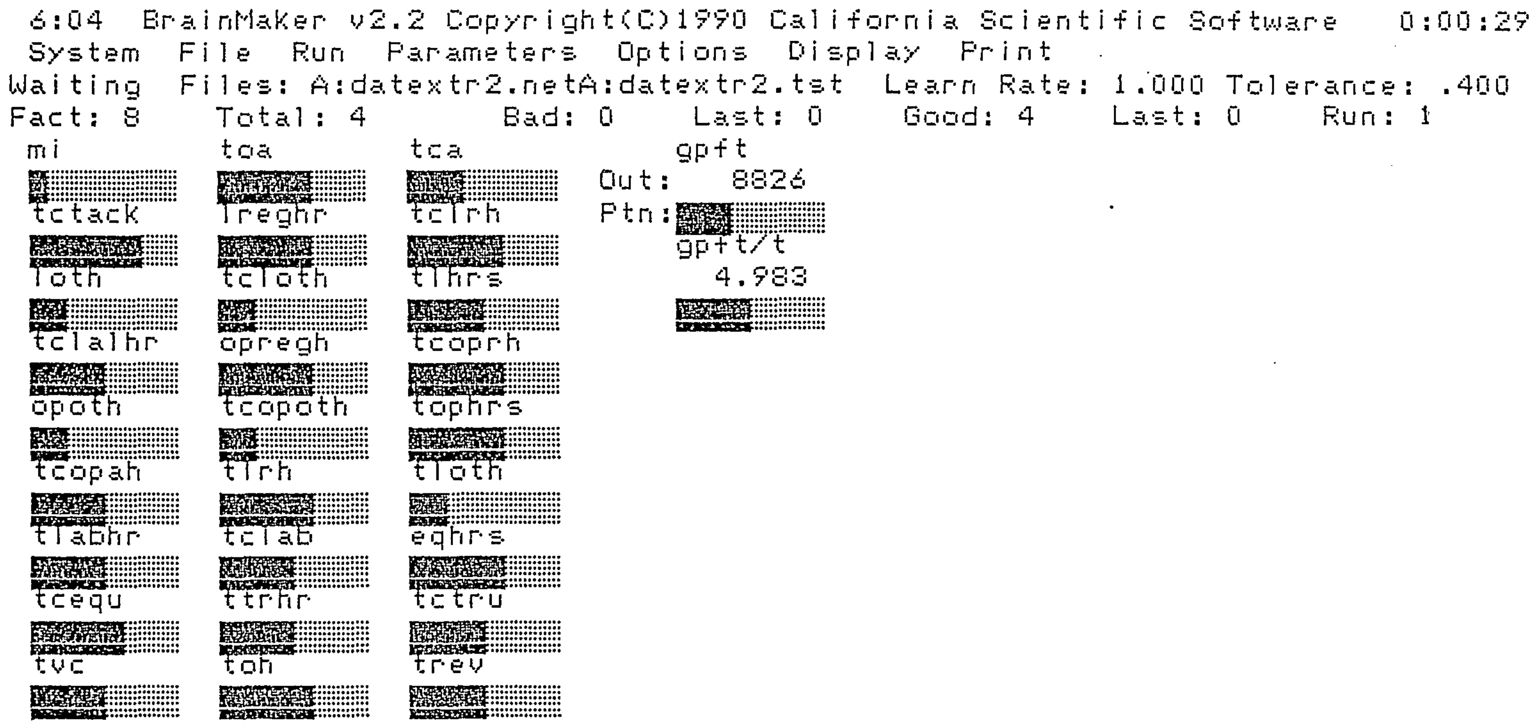


Figure 17. BrainMaker Screen Display: Test Fact 8

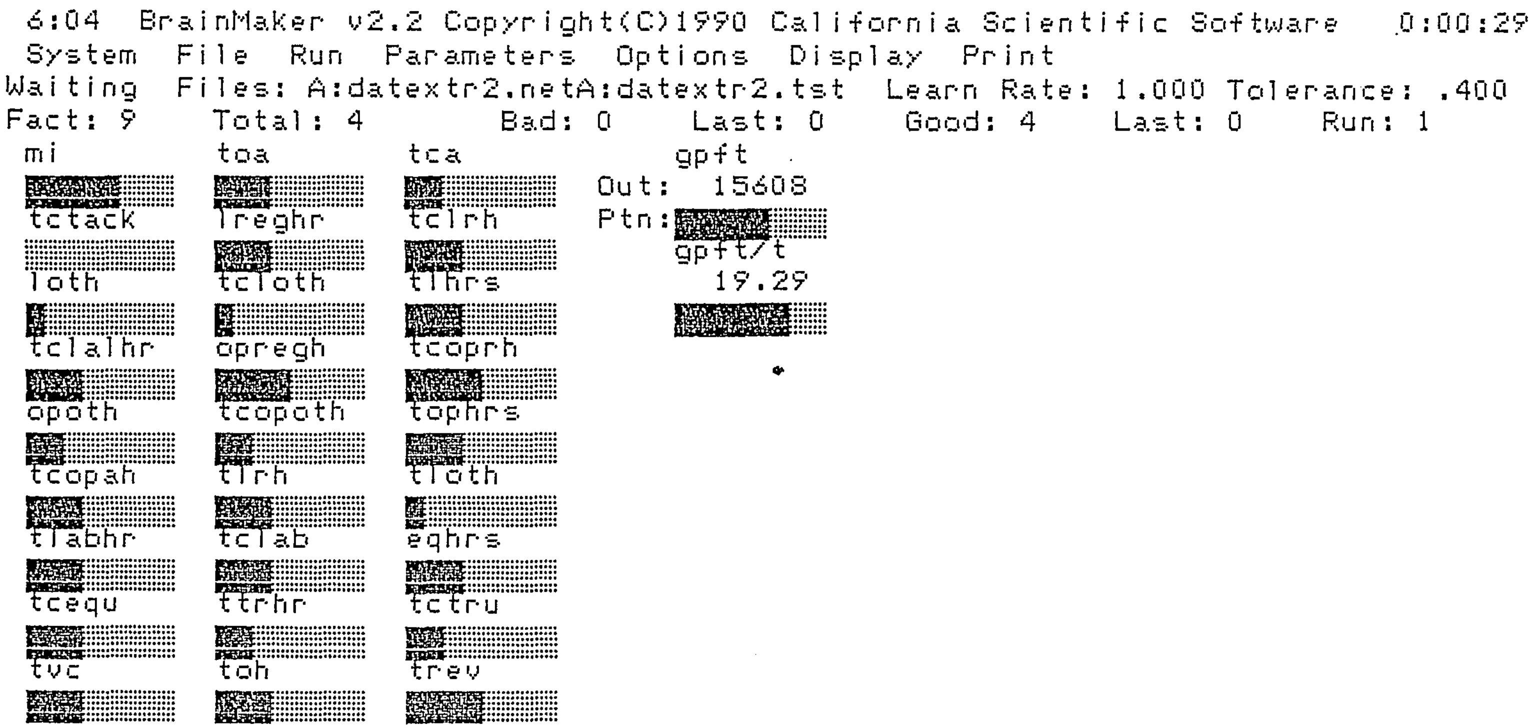


Figure 18. BrainMaker Screen Display: Test Fact 9

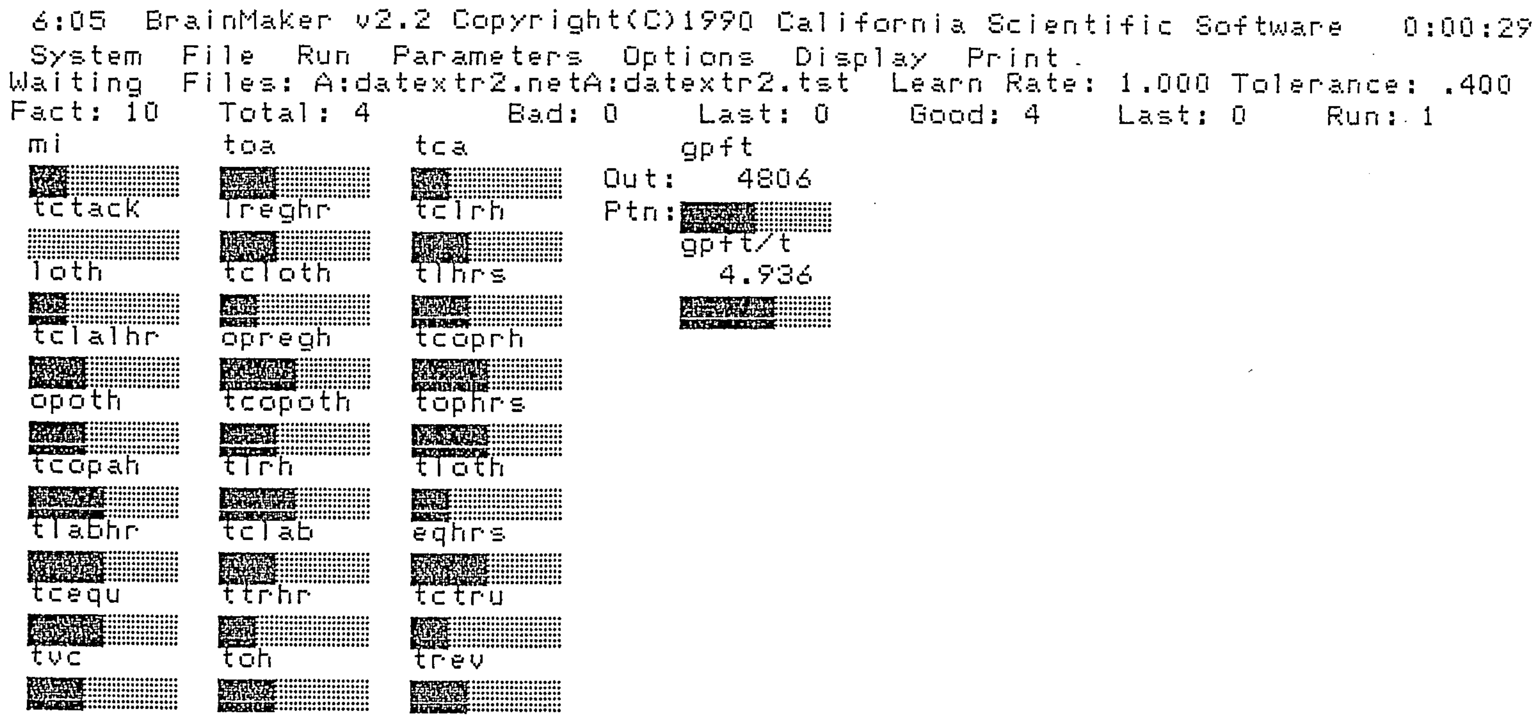


Figure 19. BrainMaker Screen Display: Test Fact 10

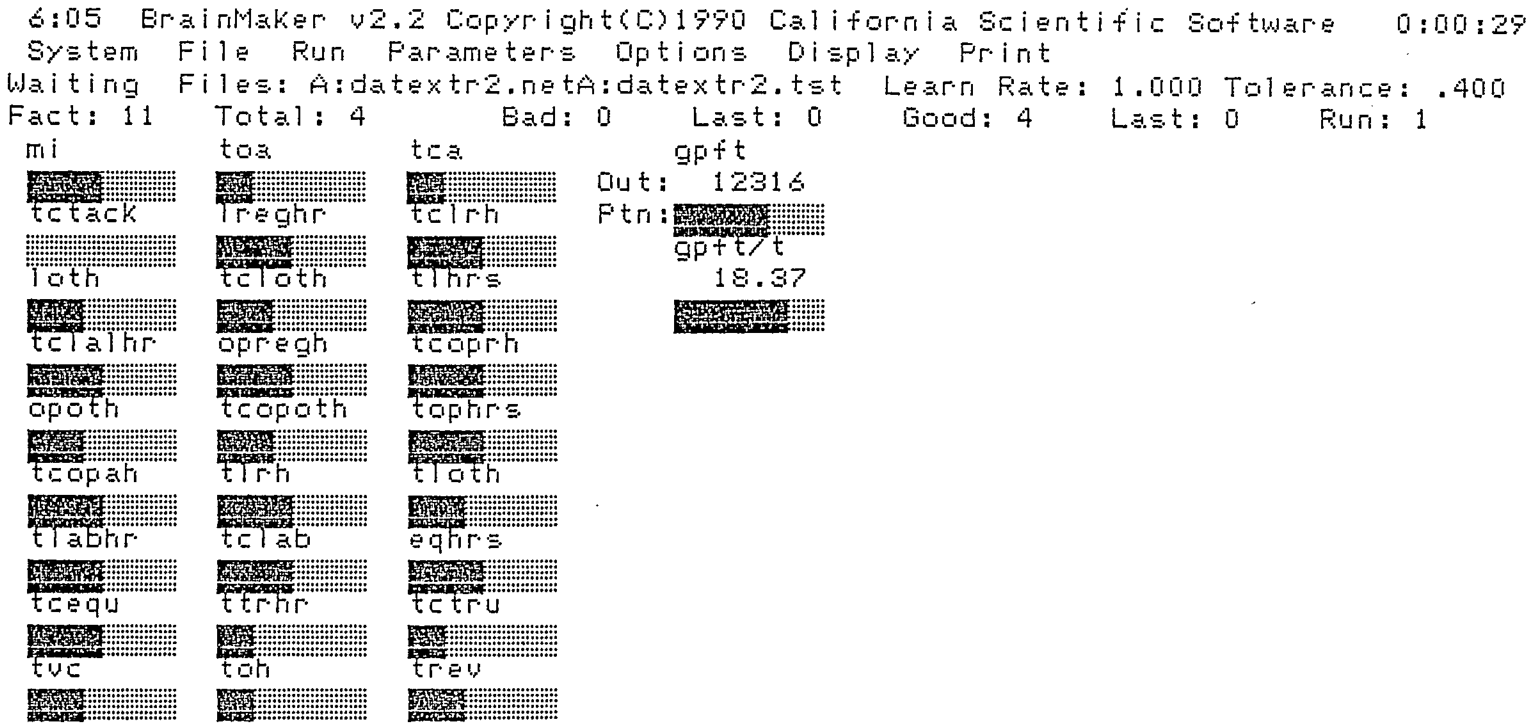


Figure 20. BrainMaker Screen Display: Test Fact 11

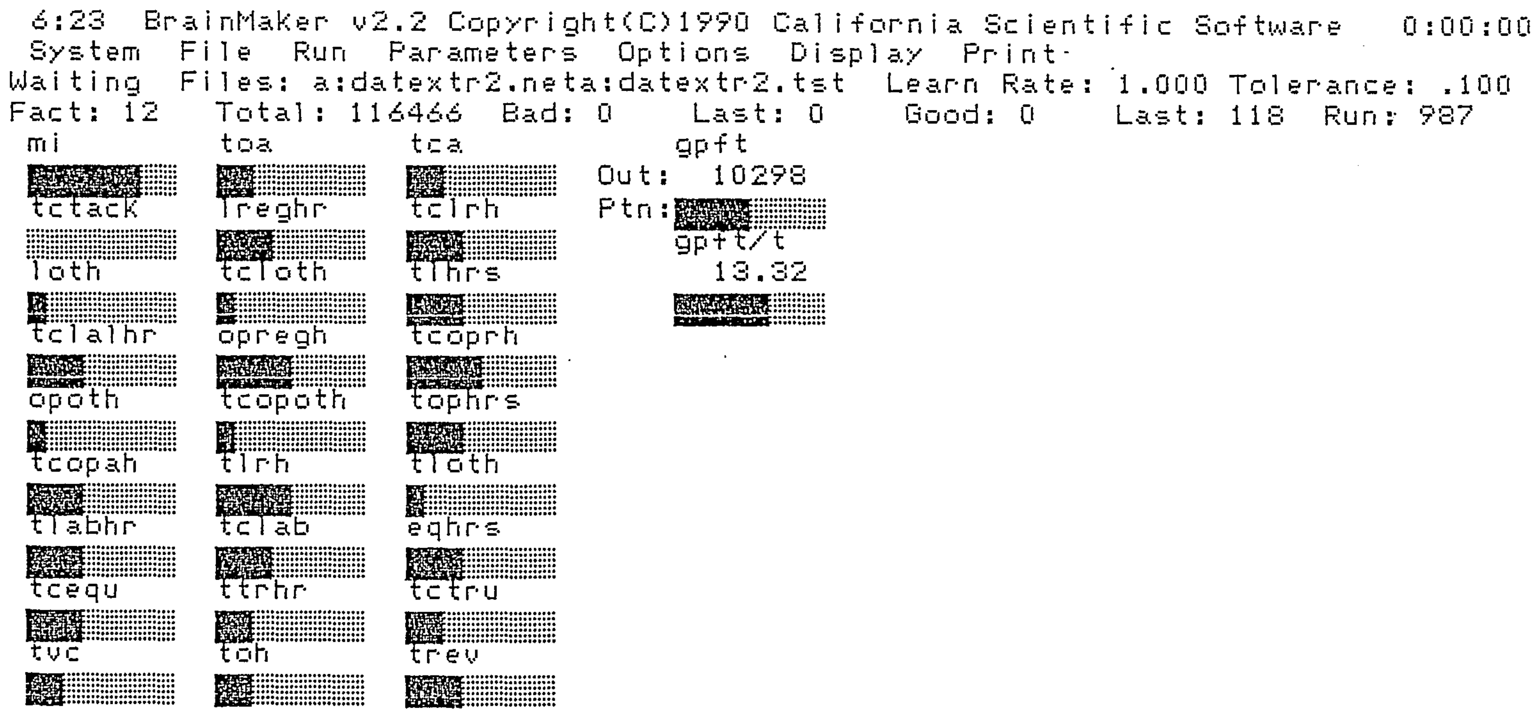


Figure 21. BrainMaker Screen Display: Test Fact 12

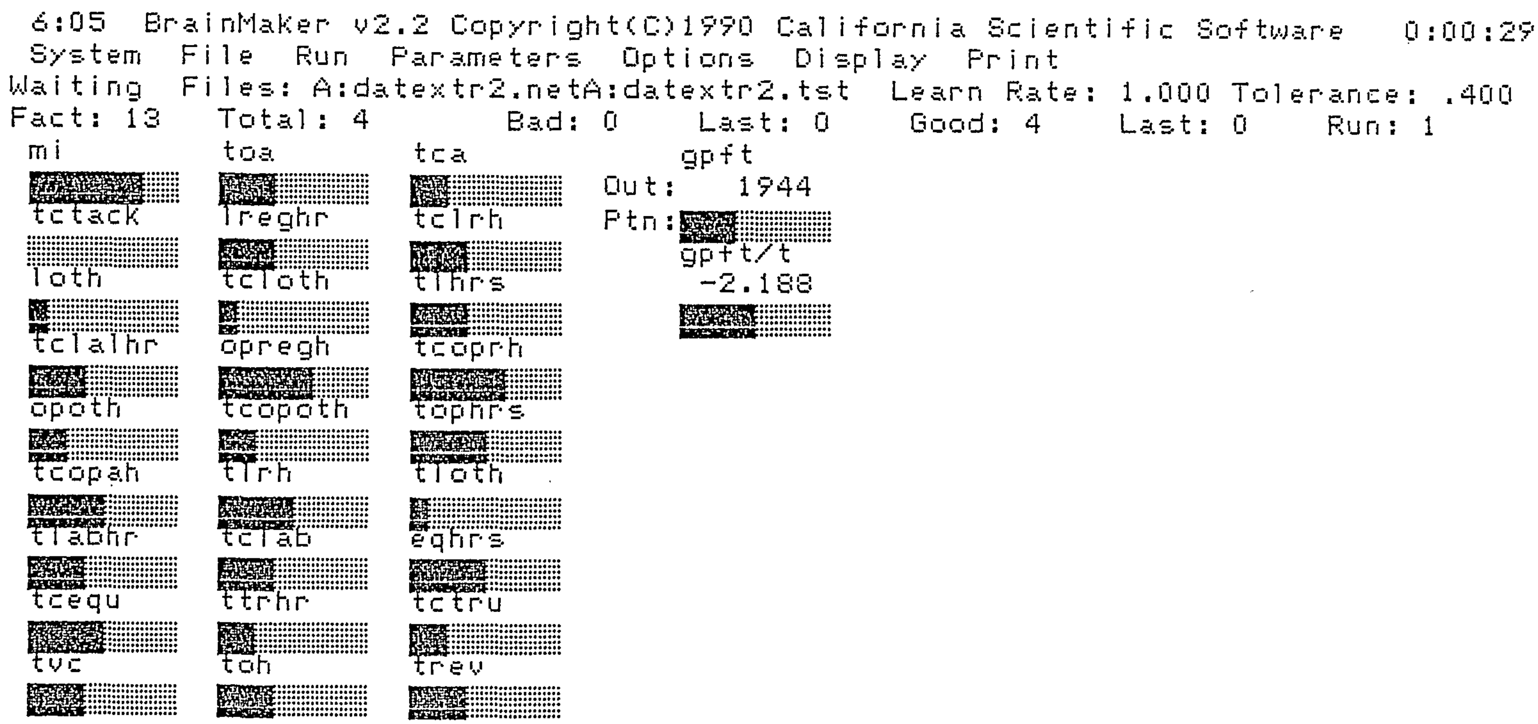


Figure 22. BrainMaker Screen Display: Test Fact 13

Figure 23. Neural Network: Calculation of Root Mean Squares for Gross Profits and Gross Profits per Ton

"NEURAL NETWORK ANALYSIS

$N := 13$

$i := 1 \,..N$

$GPTPRED_i :=$	$GPTOBS_i :=$	$GPTPRED_i - GPTOBS_i$
2589	971.4	1617.6
5103	2219.86	2883.14
9769	6046.7	3722.3
-1182	2964.39	-4146.39
-7502	-2647.8	-4854.2
10166	4423.95	5742.05
1447	-413.07	1860.07
8826	3421.67	5404.33
15608	12986.1	2621.9
4806	4996.6	-190.6
12316	12222	94
10298	8576.53	1721.47
1944	998.419	945.581

"CALCULATION OF ROOT MEAN SQUARED"

$$rms0 := \sqrt{\frac{\sum_i \left[GPTPRED_i - GPTOBS_i\right]^2}{N}}$$

$rms0 = 3304.488$

$GPTTOB_i :=$	$GPTTPRE_i :=$	$GPTTOB_i - GPTTPRE_i$
1.67	2.071	-0.401
1.1	.282	0.818
12.17	14.78	-2.61
3.92	7.437	-3.517
-10.99	5.537	-16.527
4.67	5.980	-1.31
-1.4	8.513	-9.913
1.79	4.983	-3.193
11.94	19.29	-7.35
4.73	4.936	-0.206
14.28	18.37	-4.09
10.2	13.32	-3.12
.89	-2.188	3.078

"CALCULATION OF ROOT MEAN SQUARED"

$$rms1 := \sqrt{\frac{\sum_i \left[GPTTPRE_i - GPTTOB_i\right]^2}{N}}$$

$rms1 = 6.16$

Figure 24. Neural Network Graphs of Gross Profits: Observed and Predicted Values

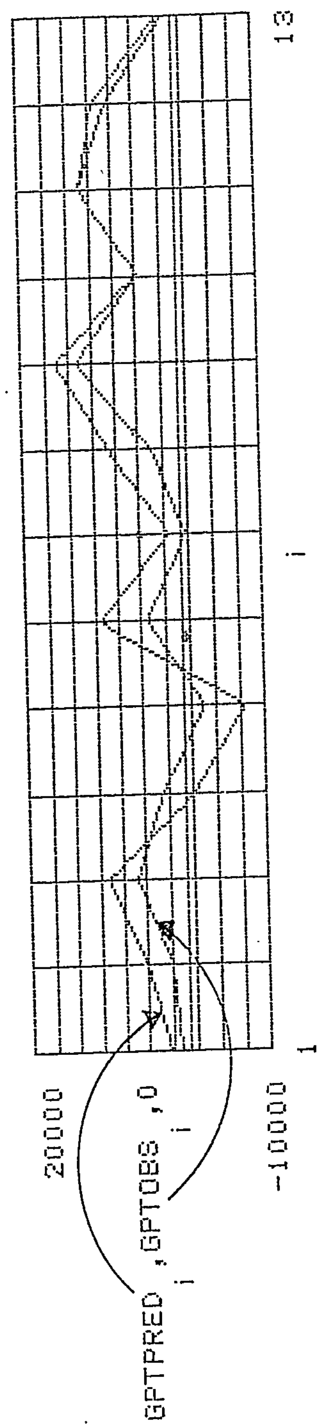
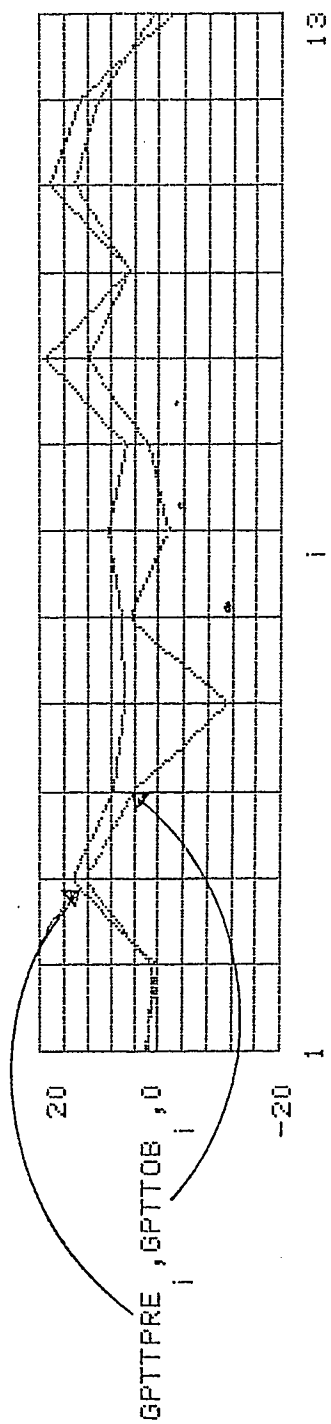


Figure 25. Neural Network Graphs of Gross Profits per Ton: Observed and Predicted Values



3. THE STATISTICAL MODEL

3.1 General Characteristics

3.1.1 Domain. General purpose, a wide variety of mathematical tasks.

3.1.2 Main general function. Display, calculation, and analysis of mathematical equations.

3.1.3 System name. MathCAD(C).

3.1.4 Dates. MathCAD was copyrighted in 1988.

3.1.5 Researchers. J. Hermann, J. Bernoff, K. Mager.

3.1.6 Location. Reading, Massachusetts, 01867.

3.1.7 Language. Not known.

3.1.8 Machine. Runs on an IBM PC or compatible or PS/2 or compatible.

3.1.9 Brief summary. MathCAD is an all-purpose system for developing a variety of mathematical applications. Numeric data is typically used. Users make choices from a menu to manage files and to make other selections, including graphs, writing equations on a screen-sized blackboard-like area.

3.1.10 Related systems. None.

3.1.11 Characterizations of givens. The system supports several types of mathematical calculations. The system includes options for displaying inputs and outputs so they can be easily seen. Data from most accounting spreadsheet type software programs can be read as input data.

3.1.12 Characterization of output. Output is typically numeric data, which can be displayed in tabular or graphic form.

3.1.13 Characterization of data. Data must necessarily be numeric data; a variety of data formats (fixed, scientific, floating point) are acceptable. No non-numeric data can be used.

3.1.14 Generic tasks. The software accepts any numeric data as inputs and outputs. Many generic tasks involving data analysis are candidates for MathCAD application. Sample programs included with software describe earth satellite motion, generate and perform a statistical analysis of a sum of random numbers perform signal processing, calculate an infinite series, and solve simultaneous equations. A special section includes problems from the fields of physics, electrical engineering, microeconomics, and operations management.

3.1.15 Theoretical commitment and reality. While not expressly stated, the software supports mathematically sound calculations and analysis. Specifically, MathCAD supports a variety of statistical analyses, including correlational analysis, matrix analysis, and regression analysis. The software documentation describes the steps involved in performing such analyses. No claims are made as to how well the predicted result of such analyses match actual results.

3.1.16 <u>Completeness</u>. The system has been fully implemented. All of the domain has been included.

3.1.17 <u>Use and performance</u>. MathCAD has been used with many real users outside the original development environment. No claims are made as to accuracy of specific predictions. There are no performance measures for external validity available, except as developed on a case-by-case basis.

3.1.18 <u>Phases</u>. The user of the system prepares the data for acceptance by MathCAD. Once the data is presented as a matrix, the raw values are converted into standardized values. The correlation matrix is computed and saved. Using the correlation matrix as input, the columns of data that represent independent variables (inputs) and dependent variables (output) are identified. A vector of standardized regression weights based on the input variables is computed. Using matrix multiplication, the standardized data matrix is multiplied by the vector to obtain the predicted values. Finally, the differences between the observed values and the predicted values (residuals) are calculated. Graphs of predicted values, observed values, and residuals are generated.

3.1.19 Subfunctions. The software also can fit a curve to a set of data presented. MathCAD has many other mathematical subfunctions.

3.1.20 Use of simulation or analysis. The system does not use any numeric simulation or analysis.

3.1.21 System/control implementation architecture. Not known.

3.1.22 Characterization of structure knowledge. MathCAD does not group knowledge except as specified by the person who uses the software. Only numeric data may be used.

3.1.23 Characterization of process knowledge. Intermediate values of partial calculations have very limited usefulness; completed steps, for example the correlational matrix, can provide insights into the multicollinearity of some of the variables under consideration.

3.1.24 Deep or surface. The system does not use "knowledge" per se; it uses data, which could be described as surface data in this case.

3.1.25 Search space. To the extent that this concept applies, MathCAD's "search space" is all the input data provided by the user.

3.1.26 Space traversal. Not applicable.

3.1.27 Search control strategy. Not applicable.

3.1.28 Standard search strategies. Not applicable.

3.1.29 Subproblems. The evaluation of partial solutions is not possible (except as noted in section 3.1.21 above).

3.1.30 Search control representation. Not applicable.

3.1.31 Search control strength. Not applicable.

3.1.32 Failure method. The system does not fail if it reaches an incorrect conclusion; any mathematically possible conclusion is acceptable. The data MathCAD uses is provided by its user and is therefore external to the calculation environment. If the calculation requested is mathematically impossible, the calculation is not completed; the user is asked to modify the calculation or the input information.

3.1.33 Uncertainty. The system has no way of checking for uncertain information (read: data). The system cannot perform the calculations if a piece of information (a value within the data set) is missing. "Knowledge" per se is not normally part of the approach used here. The result of these interacting factors is that the handling of uncertain information is ambiguous, since "uncertain" information is not identified during the calculation process, and no change in the calculation process is the result.

3.1.34 Management of uncertainty. The system does not manage uncertainty.

3.1.35 Management of time. MathCAD takes seconds or minutes to perform most of its calculations for this type of application.

3.1.36 Knowledge representation method. Numeric data.

3.1.38 Knowledge representation generality. Not applicable.

3.1.39 Knowledge structuring. In approaching regression analysis problems, MathCAD does not use a hierarchy, a network, or any other structure. The software uses matrix analysis and statistical equations to calculate its predicted values based on the data it receives. No data structuring occurs.

3.1.40 Alternative representations. Not applicable.

3.1.42 Alternative solution methods. Not applicable.

3.1.43 Optimization and multiple results. The system always produces the best answer it can (the same answer). Even if the data is presented in a slightly different order, there are no variations in its "best" (only) answer.

3.1.44 Interaction. The system has a powerful graphing feature which is easy to access, easy to use, and easy to adjust.

3.1.45 Data collection, format and acquisition. MathCAD permits the attachment of data using accounting software such as Lotus(C) or other compatible software. Data is numeric data, typically set in columns and rows. There is no expert, so there is no one from whom MathCAD acquires "knowledge" per se; note that the user of the system can choose to perform regression analysis on data that has little bearing on the values he seeks to predict. Validation of "knowledge" internally does not occur.

3.1.46 Learning. MathCAD does not "learn" from its own performance. MathCAD uses the correlations of past data presented to it to determine predictions of independently gathered data. "If the resulting predictions confrmed to observations as well, then we could believe that the regression equation reflects something about relationships in the real world" (Anderson, 1989, p. 180).

3.1.49 Explanation. MathCAD does have some ability to explain where its result came from, through an analysis of the same data using its curve fitting (multiple regression) program.

3.1.50 Strengths. MathCAD's general purpose attributes make it well-suited for mathematical applications, including financial applications. The examples of correlational and regression analysis included with the software and documentation provide ample explanation of how the software works. The examples in the more advanced chapters of the book are easy to follow, once the basics of software use have been mastered.

3.1.51 <u>Weaknesses</u>. MathCAD's major weakness is that it is presented as easy to learn. It is not. There are no clues in the introductory sections as to how long the basic concepts, the intermediate concepts, or the advanced concepts of use take to learn. The new user is "dropped off" whenever the documenters seem to stumble onto a technical writing challenge. Furthermore, customer support for its student edition is non-existent.

Continuing with the second step of Cohen and Howe's criteria (see Figure 2), we examine the use of this software as a method for solving the problem of predicting project profits.

<u>How this approach is an improvement over existing methods</u>. MathCAD could be used by the company to analyze past project data in assisting managers pricing current bids. The software itself could have other additional uses within the organization. Existing approaches such as certain statistical methods require some understanding of these methods. It is not easy for someone to use MathCAD for this type of application without their first understanding the statistical methods on which it is based.

MathCAD takes several hours to learn to use; several more hours are needed to develop the application under discussion. Development time includes data manipulation (in the style of accounting software packages) and computational development and processing. MathCAD can be used for a variety of kinds of data and problems.

Evaluating the performance of the method. There are no industry-specific or software-specific metrics currently recognized for evaluating MathCAD in this particular application area. Several other statistical methods for general error analysis may be appropriate as well.

Reliance on other methods. MathCAD does require input to be in a particular form, for example, in columns of data. Additionally, there are restrictions as to the type of data (only numeric). There are no specific constraints regarding the type of knowledge that may be represented.

Underlying assumptions. This section deals with what aspects of the research tasks have been omitted from this study. These aspects are discussed in Chapter 6.

Scope of the method. The scope of this method is extendible. The approach taken in developing this statistical model using MathCAD can be scaled up to a larger input file. The method addresses the need of managers to understand how to develop bids and to choose projects that will result in profits for the company. While the method focuses on each day's profits and not the entire project's profits, it is true that the profits of each day for that project, when summed, indeed represent that project's entire profits. By examining each day's profits, daily fluctuations can be more easily examined and analyzed.

Tasks that involve daily work on a project are represented by the task under study. Parts of these tasks could be applied to other problems, such as other kinds of construction, consulting, or engineering projects. There are also some indications that this method can be used in measuring marketing inputs (advertising) and outputs (sales).

This method also can be transferred to more complicated problems, ones involving even more input variables and output variables, and more seemingly unrelated inputs.

When MathCAD cannot provide a good solution, it may provide a bad solution. Since MathCAD can only identify certain classes of errors, it is possible to for someone using the software to unwittingly believe that a bad solution is in fact a correct one. MathCAD gives the best solution it can given the available data and other constraints.

How well the method is understood. This aspect of the method is treated in Section 2.2, Theoretical Considerations. The limitations of the method are discussed in Section 6.

Relationship between the problem and the method. The problem is a complex, dynamic one, and the parameters surrounding project profits for this asphalt paving company are not well understood. Regression analysis has historically been used with success for predicting financial information based on historical inputs. The prediction of project profits seems to be an appropriate case for this regression analysis method.

3.2 Theoretical Considerations

For a treatment of the mathematical considerations, the reader is referred to a standard statistics text, for instance, Freund, J., & Walpole, R. (1980). While the temporal issues, and the learning issues associated with the statistical model, are important, they are beyond the immediate scope of this study. The reader is referred to the literature for treatment of these considerations.

3.3 The Development of This Profit Model. The 130 cases (rows) of raw data were prepared using a standard accounting software package. Size limitations of the software package required the deletion of extra blank spaces and any clearly redundant columns of data. Any non-numeric data was deleted before transfer to MathCAD. Twelve cases were set aside for testing after the regression analysis was completed.

Twenty-nine variables were read into the MathCAD program; the first twenty-seven were the independent variables (inputs); the last two were the dependent variables (outputs).

The matrix used to the develop the correlation analysis and regression analysis was 118 rows long and 29 columns wide. This raw data matrix was turned into a standardized data matrix (see Figure 26).

To compute the correlation matrix, the standardized data matrix was premultiplied by its transpose; the result was divided by the number of cases (N=118). The resultant correlation matrix is used in the next step to develop the regression analysis.

A review of the non-diagonal values of the correlation matrix indicated the collinearity of certain variables. A review of the data indicated the redundancy of certain variables. The following steps were taken to eliminate redundancy and collinearity: The first group deleted included twelve variables measuring a variety of clearly redundant labor hours and costs: Labor Regular Hours (5); Total Cost Labor Regular Hours (6); Labor Overtime Hours (7); Total Cost

Labor Overtime Hours (8); Total Labor Hours (9); Total Cost Labor All Hours (10); Operator Regular Hours (11); Total Cost Operator Regular Hours (12); Operator Overtime Hours (13); Total Cost Operator Overtime Hours (14); Total Operator Hours (15); and Total Cost Operator All Hours (16).

Since Total Labor Regular Hours (17), and Total Labor Overtime Hours (18), were redundant with (19), Total Labor Hours, they too therefore were eliminated. Total Trucking Hours were collinear with Tons of Asphalt (2); the former variable was eliminated (23). Variable 26, Total Cost of Overhead, was collinear with the Total Cost of Trucking (24); the former was eliminated. Collinearity between two other variables (19 Total Labor Hours, and 20 Total Cost of Labor), forced the elimination of one, Total Labor Hours (19). Ten input variables and two output variables remained after this analysis was completed.

Two beta vectors, one for each of the output variables (Gross Profit (28) and Gross Profit per Ton (29)) were computed. The ten columns of input data were isolated and reassembled into a ten-column matrix. The new ten-column standardized data matrix was multiplied by each value of beta to determine predicted values of Gross Profit and Gross Profit per Ton for each row of data. (See Figures 27 and 28.)

The predicted values and the observed values for each of the two dependent variables were graphed; also, the residual values for each observed value and predicted value were graphed. (See Figures 29, 30, and 31.)

The regression weights in the beta vectors were applied to the test data (12 cases). The resulting predictions were graphed; and their residuals were graphed as well. To determine the goodness of the resulting prediction, the RMS (Root Mean Square) was calculated for both the Gross Profit predicted values and for the Gross Profit/Ton predicted values; to calculate the RMS, the residuals were squared, summed, divided by the number of cases, and the square root of the result was taken. (See Figure 32.)

Continuing with the evaluative framework of Cohen and Howe, we now evaluate the method of implementing this model (Figure 3).

<u>How the program demonstrates the method.</u> The results of the regression analysis are expressed in terms of the output variables, Gross Profits and Gross Profits/Ton for each crew day tested. These outputs can be evaluated externally by comparing these predicted values with the actual values, using several methods (we chose RMS). The internal behavior of the analysis is moderately transparent. Given a well-defined set of test cases, it is possible to

demonstrate its predictive capabilities. Twelve test cases were used.

Special tuning. No special tuning of the analysis was needed.

Implementation of the method. The implementation of the method is relatively straight-forward.

3.4 Summary of Major Findings. The calculations using MathCAD were developed and checked several times to insure accuracy. Graphs of the results and the calculations can be found in Figures 26 through 32. The final calculations develop the Root Mean Square (Figure 32). The RMS for the Gross Profits estimates was .0007052; the RMS for the Gross Profits/Ton estimates was .778.

3.5 Discussion. The values of the RMS appear to indicate a high degree of accuracy. As judged by the graphic representation of the data, the degree to which the observed and predicted values of the test cases agree seems very high. Although the model itself required considerable review before it yielded its results, those results appear to be remarkably good overall.

"REGRESSION ANALYSIS OF ASPHALT PAVING DATA"

"Read raw data matrix:"

$Y := \mathrm{READPRN}(new)$

$N := \mathrm{rows}(Y)$ $\qquad N = 118$ $\qquad$ "cases (crew days)"

$J := \mathrm{cols}(Y)$ $\qquad J = 29$ $\qquad$ "initial variables"

$i := 0 \,..\, N - 1$

$j := 0 \,..\, J - 1$ $\qquad M_j := \mathrm{mean}\left[Y^{\langle j \rangle}\right]$ $\qquad S_j := \mathrm{stdev}\left[Y^{\langle j \rangle}\right]$

$$y_{i,j} := \frac{Y_{i,j} - M_j}{S_j}$$

"Standardized data matrix:"

$\mathrm{WRITEPRN}(sdm) := y$

"Correlation Matrix:"

$$r := \frac{y^{T} \cdot y}{N}$$

$\mathrm{WRITEPRN}(corr) := r$

Figure 26. Regression Analysis: Correlation Matrix

"REGRESSION ANALYSIS OF ASPHALT PAVING COMPANY DATA"

"Retrieve the standardized data matrix and the beta weight vectors:"

```
new := READPRN(sdm)
 N := rows(new)
 N = 118
 J := cols(new)
 J = 29

Beta := READPRN(beta)
 A := rows(Beta)
 A = 10
 B := cols(Beta)
 B = 2
```

"Isolate columns 1,2,3,4,19,21,22,24,25 and 27 of sdm as ten vectors. Then, reassemble them into a ten-column matrix."

```
j := 1 ..10
```

$V1 := new^{\langle 0 \rangle}$

$V2 := new^{\langle 1 \rangle}$

$V3 := new^{\langle 2 \rangle}$

$V4 := new^{\langle 3 \rangle}$

$V19 := new^{\langle 18 \rangle}$

$V21 := new^{\langle 20 \rangle}$

$V22 := new^{\langle 21 \rangle}$

$V24 := new^{\langle 25 \rangle}$

$V25 := new^{\langle 24 \rangle}$

$V27 := new^{\langle 26 \rangle}$

Figure 27. Regression Analysis: Ten-column Matrix

Figure 28. Regression Analysis: Beta Calculations

```
Newsdm := augment(V1,V2)
Newsdm := augment(Newsdm,V3)
Newsdm := augment(Newsdm,V4)
Newsdm := augment(Newsdm,V19)
Newsdm := augment(Newsdm,V21)
Newsdm := augment(Newsdm,V22)
Newsdm := augment(Newsdm,V24)
Newsdm := augment(Newsdm,V25)
Newsdm := augment(Newsdm,V27)

W := rows(Newsdm)
W = 118
X := cols(Newsdm)
X = 10
```

"To compute ypred, the vector of predicted values, weight each row (case) of the standard data matrix by each of the beta weights."

$s := 0 \,..1$

$\text{Beta0} := \text{Beta}^{\langle 0 \rangle}$

$\text{Beta1} := \text{Beta}^{\langle 1 \rangle}$

$\text{ypred0} := \text{Newsdm} \cdot \text{Beta0}$

$\text{ypred1} := \text{Newsdm} \cdot \text{Beta1}$

"Gross Profit" "Gross Profit per Ton"

$$\text{Beta0} = \begin{bmatrix} 0.00000002365 \\ -0.225 \\ -0.0000004993 \\ 0.000000076 \\ -0.0000000771 \\ -0.0000002234 \\ 0.0000001395 \\ -0.0000002239 \\ -2.154 \\ 2.88 \end{bmatrix} \qquad \text{Beta1} = \begin{bmatrix} 0.067 \\ -0.515 \\ -4.393 \\ -0.093 \\ -0.509 \\ -0.009 \\ -0.233 \\ -0.902 \\ 3.559 \\ 2.662 \end{bmatrix}$$

Figure 29. Regression Analysis: Residual Calculations

"The actual standardized values of V28 and V29, gross profit and gross profit per ton, are found in the last two columns of sdm:"

$i := 0 \,..117$

$k := 0 \,..117$

$yobs0_i := new_{i,27}$ $\qquad$ $residual0_i := yobs0_i - ypred0_i$

$yobs1_i := new_{i,28}$ $\qquad$ $residual1_i := yobs1_i - ypred1_i$

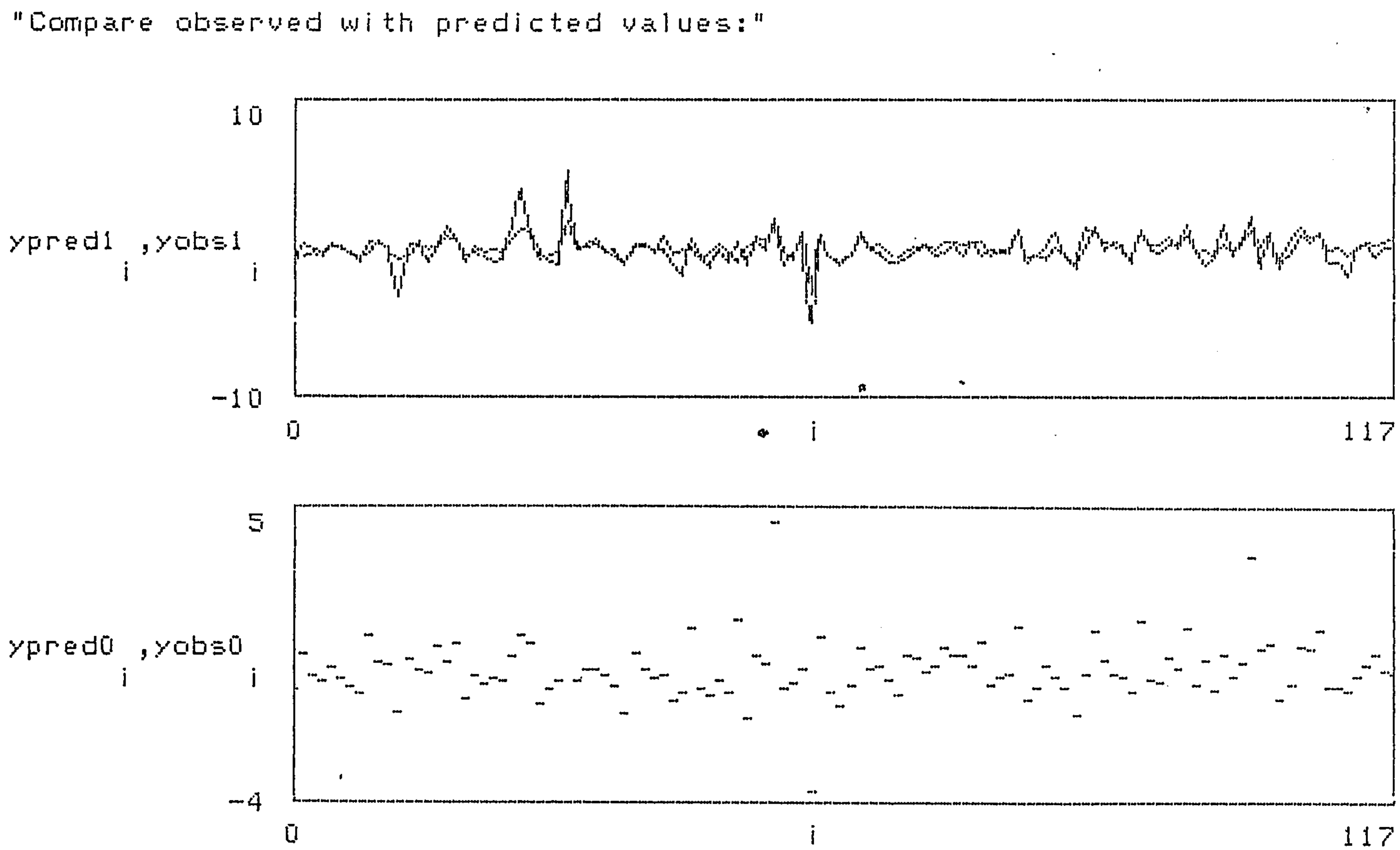


Figure 30. Regression Analysis Graphs of Gross Profits: Observed, Predicted, and Residual Values

Figure 31. Regression Analysis Graphs of Gross Profits per Ton: Observed, Predicted, and Residual Values

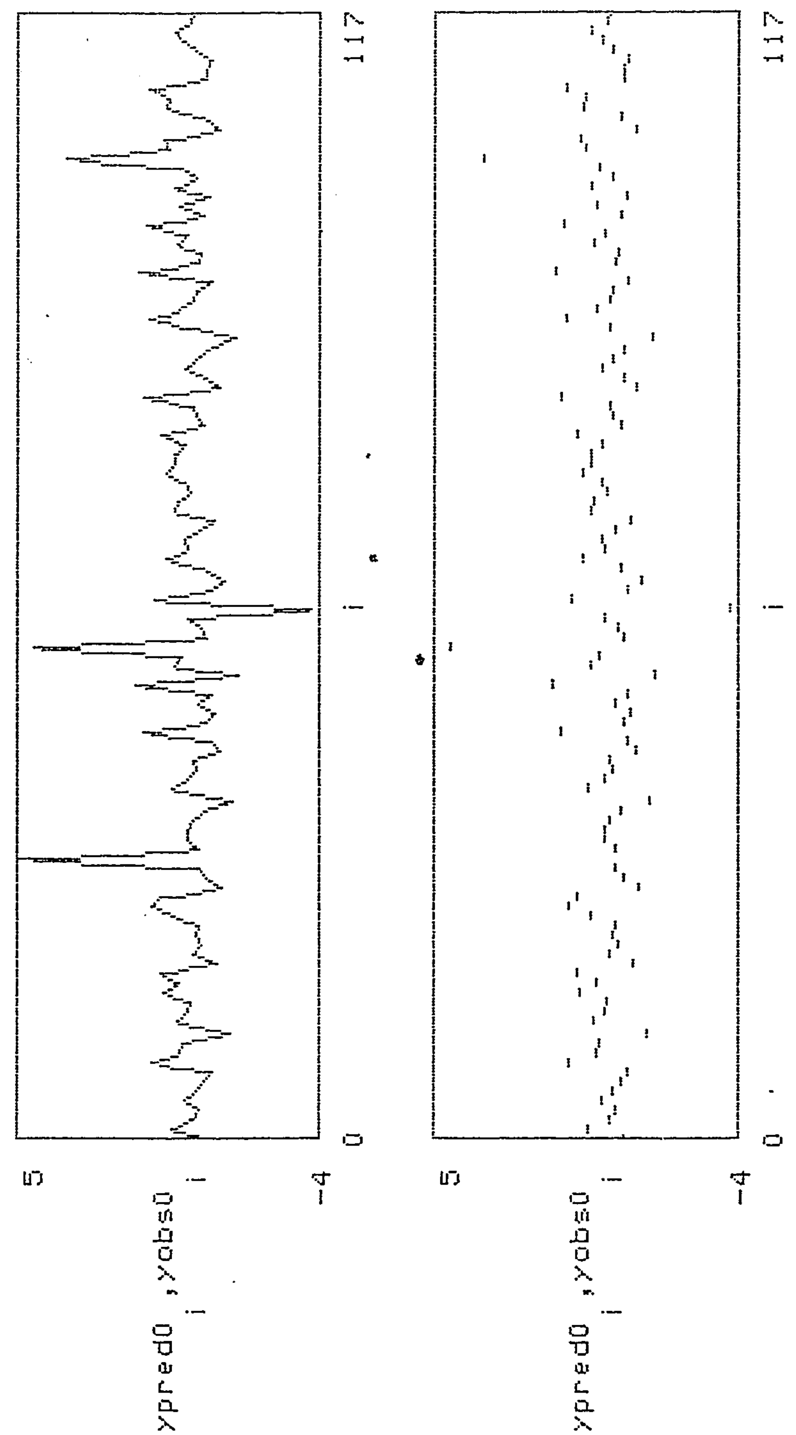


Figure 32. Regression Analysis: Calculation of Root Mean Squares for Gross Profits and for Gross Profits per Ton

"Calculation of Root Mean Squared"

$N = 118$

$$rms0 := \sqrt{\frac{\sum_i \left[residual0_i\right]^2}{N}}$$

$$rms1 := \sqrt{\frac{\sum_i \left[residual1_i\right]^2}{N}}$$

$rms0 = 7.052 \cdot 10^{-4}$

$rms1 = 0.778$

4. COMPARATIVE ANALYSIS

4.1 Introduction.

In this section, we discuss several comparative approaches that are available for evaluating the performance of the AI-based and statistical models that have been developed. To facilitate discussion, these two methods have been grouped into two categories, quantitative approaches and qualitative approaches.

4.2 Quantitative Approaches

4.2.1 Introduction

In this section, we discuss the use of several quantitative approaches to evaluating the performance of AI-based models. These approaches are: Return on Investment (ROI); Sassone's Hedonic Approach; Reliability; and Validity. A summary of the discussion follows these overviews.

4.2.2 Return on Investment (ROI)

In the review of the literature, opinions seemed mixed regarding the use of ROI for evaluating the effectiveness of AI technology. In evaluating the neural network model and the statistical model, however, ROI can be used in several ways to measure performance. First, ROI can be used to evaluate certain <u>outputs of the respective models</u>. ROI, for instance, could be the output variable of either model under appropriate domain conditions. Second, it is possible to use ROI to assist in the management decision to purchase AI-based technology. Admittedly, the terms "return" and "investment" might themselves be re-evaluated in the process. Many of the current tangible benefits associated with several newer technologies are former intangible benefits. The increased use of conventional and advanced technologies make available data that used to be unavailable within organizations. Furthermore, we note the emergence of client-centered marketing concepts, and the development of management control systems. Such developments have facilitated the ability of managers to successfully demonstrate the return on such investments by using measures such as ROI.

4.2.3 Sassone's Hedonic Approach

The approach of P. Sassone (1986, 1987) and others in developing a metric for justifying office automation systems has potential application to our models. This approach measures both effectiveness and efficiency. It is this effectiveness increase brought about by use of automated technology that is described as especially difficult to measure.

Briefly, this method involves several phases. In the first phase, the activities of various personnel are grouped by employee type. In the second phase, using a pencil-and-paper log, all personnel record their daily work activities. The recording schedule is designed to account for unusual departmental circumstances and for unproductive time. In the third phase a matrix of baseline activity for each employee is developed. This matrix establishes the value of the labor of each employee. In the fourth phase, this value in terms of labor is translated into value in terms of cost, using wage equations. The decrease in amount of time needed to perform the same activities is estimated in the fifth stage; this estimated pre-office automation value becomes the estimated post-automation value, should the automation occur.

The term "hedonic" refers to the concept of the greatest good. Sassone's hedonic approach attempts to quantify many of the benefits of technology that have been described as elusive. If the neural network model or the statistical model to be used at the asphalt paving company, Sassone's approach could be used to determine the value of the investment a priori. The advantage of Sassone's approach is that it appears to succeed in measuring the quality and the quantity of the work performed. It would be appropriate to add such factors as learning time and opportunity costs to such models for completeness's sake. Both the neural network and the statistical model could be evaluated using a modified version of Sassone's approach.

4.2.4 Reliability

Quantitative measures of reliability of expert systems have appeared in the literature for several years

(Hollnagel, 1989). Measures have included the number of errors found per n lines, and development of the measure of the probability of an error occurring under certain circumstances. Increased testing can increase the reliability of a system. It is also possible to test a cross-section of representative input combinations; less feasible is the testing of all input combinations over a given test condition or knowledge domain. The question of responsibility for inadequate or incomplete testing is also of concern here. The question of responsibility is especially appropriate when the consequences of failure may be non-trivial. Each system could be measured against the criteria of reliability; each test would require, for instance, larger training and sample data pools. Each model must be reliable; a project with a low chance of profitability must be clearly and quickly identified, preferably before the bid is made and accepted. To measure this reliability, the "proving" software correctness (Hollnagel, 1989) has been suggested, though these approaches appear to be time-intensive. How the two models determine their results is important in determining their reliability, too.

4.2.5 Validity

The question of empirical validity deals with the comparisons of the results from the model(s) with the results observed in the real world. A variety of statistical measures and methodologies, some more appropriate than others, can be included in determining the validity of the results of these models.

It is possible to measure the performance of these models by determining the "percentage correct" during the testing phase. Such a measure might be appropriate if the behavior of the system under consideration were stochastic. However as has already been established by Berry (1990), a prior statistical analysis demonstrated elusive conclusions. Given the experimental nature of this study, and the dynamic nature of the data under study, a more appropriate measure is the Mean Root Square.

The validity of each model could also be established using other criteria, for instance, the cost estimates of a manager.

4.2.6 Summary

Several quantitative approaches to evaluating the performance of the neural network and statistical model have been suggested in the above section. This list is not conclusive; other quantitative metrics for performance may also be appropriate.

4.3 Qualitative Approaches

4.3.1 Introduction

In this section, several of the less easily quantified concerns surrounding use of AI-based technology are addressed. These include the issues of usability, cognitive style, the use of models to make policy, the perceived reliability of models, and the perceived validity of models. Each approach will be discussed in turn. Finally, the approaches will be summarized.

4.3.2 Usability Issues

In the review of the literature and in the description of each model under consideration, usability of AI-based and other software is increasingly important. Hollnagel (1989) suggests the following criteria for evaluating usability:

> ...the correctness of the final decision; the accuracy of the final decision; the correctness of the reasoning techniques; sensitivity; robustness; the quality of the human-computer interaction; and the cost-effectivenss of the system (Hollnagel, 1989, pp. 176-179).

As has been mentioned earlier, usability is even more important where AI-based systems are involved. Again, it is important to separate issues of ease of use from issues of the epistemological truthfulness of the model. Even when highly accurate statistical models can be reliably and easily used, their epistemological truthfulness may remain an enigma. Moreover, an epistemologically truthful model potentially may be unusable. The evaluation of models for usability can occur by several methods, among them, certain protocol analysis methodologies (Shneiderman, 1980), and the "thinking aloud" method developed at the

IBM Watson Research Laboratories. Usability may be evaluated by experimental methods, and by survey methods.

4.3.3 Cognitive Styles

According to Shneiderman, "interest in the more psychological aspects of human performance variation has led to research into cognitive style" (1980, p. 56). Shneiderman cites the work of Doktor (1976) regarding two poles of information processing:

> The two poles are analytic and heuristic. Analytic implies sequential, linear, and verbal symbolic processing, or left-brain oriented, and heuristic means intuitive, global, pictorial processing, or right-brain oriented. Difficulty in implementing management information systems can be the result of <u>cognitive style mis-matches</u> [italics added] between users and information design. (Shneiderman, 1980, p. 56).

While the topic of cognitive style of computer users is itself controversial in the literature, it appears to have bearing on the matter of comparison of two models. It is possible that cognitive style differences may play a large role in determining which model gains acceptance in the work environment. We can find relevance in Doktor's modes of analytic and heuristic. Perhaps engineers and managers, respectively, would make different choices based on characteristics of the model: engineers might select the statistical model, and managers might select the neural network model.

Furthermore, in research on building project teams, Couger and Zawacki (1978, in Shneiderman, 1980,

p. 124) note that "personality studies of programmers still show their social need for interaction is significantly lower than for many other professionals". Given the research already performed in this area (for example, Zmud, 1979), it might be useful to attempt to match the cognitive style of the software with that of its user population.

4.3.4 Good Models, Bad Policy, Vice Versa

One prominent researcher exploring the impact of computer systems on organizations suggests that such information technologies lay open new opportunities for control which managers discover and decide to exploit (Zuboff, 1988, p. 314).

A good model may be used to support bad policy decisions, decisions which ultimately may lead to the company's failure. Furthermore, a model that "predicts poorly" may actually foster organizational changes, redistribution of information, cooperation, and ultimately the development of good policy (Perolle, 1990).

4.3.5 Perceived Reliability

Perceived reliability can be measured by assessing the perceptions of potential users and the perceptions of actual users. A simple research design, including interviews and/or questionnaires, can help to measure this variable for the neural network and the statistical model.

4.3.6 Perceived Validity

Perceived validity can be measured by assessing the perceptions of potential and actual users. A research design including interviews and/or questionnaires can assist in obtaining measures of this variable for both models.

4.3.7 Summary

The measure of qualitative performance variables of AI-based models affects all classes of users. The ease of use of the system, the cognitive style of its users, the way in which the models are used to shape policy, and the perceived reliability and validity of the models are often acceptance factors that are overlooked or underestimated.

In this section we have attempted to describe how these qualitative criteria can serve as important factors in evaluating the performance of an AI-based model.

5. SUMMARY OF MAJOR FINDINGS

We begin by evaluating the design of this experiment, as summarized by Figure 4 of Cohen & Howe's framework.

Demonstration of examples. The neural network model demonstrates 13 examples; the statistical model 12. The test examples used in both models are not qualitatively different. The examples illustrate that the performance of the neural network requires further research. Furthermore, the examples illustrate the amount of development time and effort which may be needed in order to use this model successfully for this application. Notably, the use of fewer than 200 training facts is considered somewhat low, according to the documentation accompanying this neural network software. It appears that the number of examples used, both for training and for testing, was inadequate.

Comparison of model's performance to a standard. The neural network's performance could be compared to another program, experts, novices, or its own tuned performance. In this study, the neural network's performance is compared to the performance of a statistical model. The standard against which the model's performance is measured is an outcome based on real data: actual profits of a particular crew day.

Criteria. The criteria for good performance was selected by the researcher. Good performance of the neural network model is considered to be performance that is as good as or better than performance obtained with the statistical model.

Domain independence. BrainMaker is purportedly general in purpose. This particular application could be tested in similar domains; however, the results of such tests are not known. Other domains are to varying degrees qualitatively different. However, the class of asphalt paving construction projects appears well represented. The performance of this program in this domain may not be compared necessarily to performance in other domains.

Evaluation of a series of related programs. Several different sets of training parameters were investigated. As learning tolerances were loosened, errors increased. As learning tolerances were tightened, training time increased; with it the possibility of training the network appeared less likely. The length of time involved in training the network at the .02 training tolerance seemed to suggest that the network would be unable to learn at this training tolerance.

In the following section, we will discuss what this experiment told us. The headings in this section are suggested by the work of Cohen & Howe (Figure 5).

Program performance when compared to its selected standard. The neural network did not perform well when compared to its selected standard at the .1 training and the .4 testing tolerances. The RMS of the neural network was several orders of magnitude larger than the RMS for the statistical model.

Different from predictions. It was expected that the neural network's performance would be better than the results actually indicated.

Efficiency of space and knowledge requirements. Not known.

Demonstration of good performance. The neural network model did not demonstrate good performance as measured by our standard.

What was learned? The experiment using these two models helped us learn that the comparison of the neural network model and the statistical model is not a simple matter. Each model has unique characteristics that can be explored in industrial applications. This exploration is an area for future research.

Ease of understanding. Neither BrainMaker nor the MathCAD model would be considered easy for the intended users to understand. Both software models require several hours each of reading, tutoring, and trial-and-error use before reliable use can be expected. This time is in addition to any time needed to actually develop the particular application.

Performance limitations. Apart from the number of neurons (512), connections per layer (32767), number of layers (8), characters in an input line (4096) and its mixed data restriction, in the standard version, BrainMaker has no other known performance limitations.

Why the program works. It is the author's belief that the neural network's results were so inaccurate for two main reasons. First, because the number of facts use to train the network was very low. Second, because the learning tolerances were set very high (.1) compared, for instance, to the profit margin for a typical project (.03 to .05). The neural network model's learning parameters were changed slightly in an effort to see if its accuracy could be improved somewhat.

Several program responses were not explored in using the neural network model. These include: the addition of noise to the data, the rearrangement of input, the increase in the amount of missing data. However, the use of different training and testing tolerances was explored.

Characteristics of test problems and performance. The test problems were considered typical crew days; the selection of every 10th case was not random; data was arranged in chronological order, and a range of days implied a good distribution of temperature and weather conditions between February and December of

1988. Since training tolerances were set so large, several predictions resulted in sign-differences between the two output variables (Gross Profits and Gross Profits per Ton). This seemed troubling until the training tolerances were reviewed in conjunction with the training data.

The results of the Root Mean Square calculations demonstrated the differences (several orders of magnitude) in the performances of the neural network model and the statistical model that were studied here. By understanding the sensitivity of the neural network model to the training tolerance, we can explore alternative training levels.

It is important to stress the role that the bidding price plays in predicting the profitability of a project. We have described the process by which the bidding price is determined: a flat percentage is added to the estimated cost, based on "the going rate" in the marketplace. By using historical data, we have pre-selected projects for which the bid was already determined in this manner. Because we have no data regarding the original cost estimate and the mark-up, we have no way of separating factors related to the original estimate and mark-up from the actual cost. In other words, since the current model does not contain bid data, the current model includes no feedback loop comparing the estimated costs and profits to the actual costs and profits for a given crew day.

An improved version of the existing neural network model would use the bid cost as one of several input variables, and would attempt to predict the actual cost. In this way, the network would attempt to show the relationship between estimated project costs and actual project costs.

6. LIMITATIONS AND ASSUMPTIONS

6.1 Neural Network Model

The BrainMaker software (standard version) is limited to 512 neurons per layer, 32,767 connections per layer, 8 layers, and 4096 characters in an input line.

The neural network model did not support intermediate or partial solutions, as discussed earlier. Nor did the software permit the mixing of numeric and symbolic data. These limitations hampered efforts to use potentially important input data. Data such as weather descriptions and the names of the foremen on the jobs may have potential for improving the model's performance.

Only a limited number of training and testing values were selected for study. In some cases, time prevented a more complete exploration of some additional values for the setting of these parameters. There may be unknown errors in the software used to develop the model, introducing error into the results obtained.

6.2 Statistical Approach

While the model seems appropriate for this data and this problem, there may be reasons why this model should not in fact be used (for instance, inconsistency between model and behavior of system under study).

There may be unknown errors in the software used to develop the model which affect the results obtained.

6.3 The Proposed Study

In the development of this study, we have chosen what we believe is a representative sample of recent data from an asphalt paving company. The degree to which these results may be generalized to other asphalt paving companies, other construction companies, or other project environments is not known.

While the data was checked for accuracy, it is possible that some of the actual reported data is not correct. There may be, for instance, errors in the estimated mileage to and from each work site.

Additional data from the asphalt paving company may have proven useful in developing either or both models. Analysis was limited to the data available.

Samples represent approximately 10% of the total data set. This data may not be representative of more recent profit behavior in the asphalt paving industry.

7. RECOMMENDATIONS FOR FURTHER RESEARCH

This study has attempted to propose a model for evaluating the performance of an AI-based model and a statistical model for measuring the profits of an asphalt paving company. Several areas of additional research are suggested.

Additional exploration of the existing model and some of the learning parameters used in this study needs to continue. Perhaps thousands instead of hundreds of input facts during the network's training phase might produce variations in performance.

Little appears to be known about how many facts is enough to ensure a particular level of system performance. What parameters determine how many facts are enough to specify a particular performance level? Research to begin to answer this question would certainly be an appropriate area for additional exploration. Furthermore, concern regarding how much time the network takes to converge is a related important area. Perhaps a damping model would eventually describe this dynamic behavior, with oscillation occurring as a percentage of the training facts. It appears clear in this study that not enough training facts were used. Under what specific conditions can the training a particular network be stopped by the researcher (or user), since no additional training would improve the availability of the result?

Another area to explore is the addition of noise to the existing learning parameters. It is suspected that there may be diametrically opposed facts in the training set used in this study. Therefore, perhaps the addition of noise to the training parameters would help the network to generalize the facts it is learning.

Furthermore, the use of a variety of neural network models, learning algorithms, and statistical models might provide interesting performance insights in this and other case studies. Perhaps the use of software supporting the use of both numeric and non-numeric data to the existing model would enhance the network's performance.

Comparisons of the performance of neural networks, expert systems, and statistical models with this case study's data, as well as with data from other types of construction projects could be performed. Such studies might point toward some general trends among construction projects in general. Such a comparison might also provide a basis for generalizing regarding the performance of specific models, the setting of specific parameters, and the use of specific data for certain classes of applications. Furthermore, such a comparison would help researchers determine the limits of such generalizations.

Opportunities to research frameworks, metrics, and methodologies for studying AI-based performance exist. The evaluative framework used in this paper was developed by Cohen & Howe (1988). This methodology seems to be one of the few proposed in the AI literature to date. It is important that a metric be selected a priori to measure the performance of AI-based models. It is also important that a methodology be selected a priori to evaluate the performance of AI-based models. The limits of this and other methodologies need to be explored through their use. The need to evaluate the performance of these models continues to be great.

8. APPENDIX

LINE NUMBER	JOB NUMBER	DATE	FOREMAN	WEATHER	TRUCKING DISTANCE (MILES)	TONS OF ASPHALT
1	D17	25-Feb-88			22.00	263.56
2	E88	14-Mar-88	MEL	SUNNY	5.50	1901.00
3	E61	30-Mar-88			5.50	811.77
4	E61	31-Mar-88			21.30	1828.59
5	E79	07-Apr-88	RAY	RAIN	14.40	830.15
6	E61	07-Apr-88			23.00	580.77
7	D25	11-Apr-88	RAY	FAIR	16.00	851.00
8	E83	22-Apr-88	RAY	FAIR	20.90	497.92
9	C75	30-Apr-88			.90	2096.89
10	C75	02-May-88	MEL	PARTLYCLOUDY50	.90	2381.41
11	D16	03-May-88	MIKE		26.80	1171.00
12	E84	03-May-88	RAY	FAIR	14.10	1362.30
13	D17	05-May-88	MEL	CLOUDY/RAIN40	22.00	315.17
14	C75	12-May-88	RAY	FAIR	.90	1334.70
15	D15	20-May-88			35.00	836.23
16	E84	26-May-88	RAY	FAIR	14.10	2018.22
17	D17	04-Jun-88	MEL	SUNNY	22.00	2392.80
18	D07	07-Jun-88	MIKE	SHOWERS70	22.50	385.11
19	E84	10-Jun-88	MEL	SUNNY	14.10	1510.43
20	D16	14-Jun-88	MIKE	SUNNY95	26.80	288.90
21	D25	16-Jun-88	MIKE	SUNNY90	18.90	734.48
22	D18	20-Jun-88	MEL	PARTLYCLOUDY80	17.00	1027.88
23	D27	22-Jun-88	MIKE	SUNNY70	11.10	1005.06
24	C75	07-Jul-88	RAY	SUNNYHOT	.90	1194.87
25	E84	07-Jul-88	RAY	FAIR	14.10	1455.09
26	E32	09-Jul-88	MEL	SUNNYHOT	15.90	496.96
27	D26	11-Jul-88	MIKE	SUNNY95	20.80	354.84
28	D36	16-Jul-88	MIKE	95.00	15.00	1021.97
29	E84	18-Jul-88	RAY	FAIR	14.10	1417.71
30	D16	25-Jul-88	MIKE	SUNNY85	26.80	1127.90
31	E84	25-Jul-88	RAY	FAIR	14.10	1341.94
32	E84	29-Jul-88	RAY	FAIR	14.10	1643.40
33	D17	30-Jul-88	MIKE	SUNNY100	22.00	2717.82
34	D16	04-Aug-88	MEL	SUNNY	26.80	761.47
35	D24	08-Aug-88	MIKE	SUNNY90	26.40	1237.43
36	E37	11-Aug-88	RAY	FAIR	22.00	755.59
37	D17	11-Aug-88	MEL	SUNNY90	22.00	1580.06
38	C95	16-Aug-88	MIKE	SUNNY95	20.90	325.55
39	E84	17-Aug-88	MIKE	SUNNY95	14.10	1084.56
40	E84	25-Aug-88	RAY	FAIR	14.10	2353.98
41	D17	25-Aug-88	MEL	PARTLYCLOUDY	22.00	2113.00
42	D24	25-Aug-88	MIKE	SUNNY80	26.40	1370.43
43	D17	01-Sep-88	MEL	SUNNY	22.00	1469.01
44	D16	06-Sep-88	MIKE	SUNNY80	26.80	1030.20
45	E84	06-Sep-88	RAY	FAIR	14.10	683.51
46	E70	08-Sep-88	MEL	SUNNY	23.40	240.98
47	D37	12-Sep-88	RAY	FAIR	8.80	2035.93
48	E84	16-Sep-88	RAY	FAIR	14.10	1291.51
49	D16	20-Sep-88	MEL	CLOUDY	26.80	389.15
50	E27	23-Sep-88	RAY	FAIR	25.50	378.34
51	D51	23-Sep-88	MIKE	SUNNY80	31.90	227.07
52	E82	06-Oct-88	MIKE	SUNNY	20.90	495.14

APPENDIX(Continued)

53	C76	08-Oct-88	RAY	FAIR	.90	3136.11
54	E84	12-Oct-88	RAY	FAIR	14.10	1383.40
55	E27	12-Oct-88	MEL	PARTLYCLOUDY	25.50	748.21
56	D37	14-Oct-88	MIKE	SUNNY55	8.80	948.12
57	D39	15-Oct-88	MIKE/MEL	SUNNY60	8.00	2806.64
58	C76	17-Oct-88	RAY	FAIR	.90	171.47
59	E84	20-Oct-88	RAY	FAIR	14.10	1497.75
60	C76	03-Nov-88	RAY		.90	2252.89
61	D39	04-Nov-88	MIKE	SUNNY60	8.00	627.43
62	D58	08-Nov-88	MEL	CLOUDY40	24.00	772.73
63	D66	22-Nov-88	MEL	SUNNY	18.30	1310.62
64	E84	23-Nov-88	RAY	FAIR	14.10	1160.06
65	D47	16-Dec-88	MEL	SUNNY/COLD	35.50	835.06
66	E77	02-Feb-88	MEL	RAIN	1.00	295.89
67	E95	09-Feb-88	MEL	SUNNY	15.80	724.76
68	E61	15-Mar-88	RAY	FAIR	21.30	1523.31
69	E88	15-Mar-88	MEL	SUNNY	5.50	1051.00
70	E61	16-Mar-88	RAY	FAIR	21.30	1289.00
71	E61	17-Mar-88	RAY	FAIR/COOL/WINDY	21.30	1844.81
72	E61	18-Mar-88	MEL	CLOUDY/COOL	21.30	1137.19
73	D17	28-Mar-88	MEL	CLOUDY	22.00	3137.00
74	E88	29-Mar-88	RAY	FAIR	5.50	2056.56
75	E61	29-Mar-88			21.30	587.34
76	E88	30-Mar-88	MEL	FAIR	5.50	1913.00
77	C75	18-Apr-88			.90	1685.92
78	E70	18-Apr-88	MEL	SHOWERS60	23.40	1180.04
79	C75	19-Apr-88	MEL	PCLOUDY50	.90	1392.90
80	D05	25-Apr-88	MEL	SUNNY55	23.00	1055.97
81	D16	27-Apr-88	MIKE	RAIN60	26.80	796.45
82	C75	29-Apr-88			.90	1814.62
83	D17	13-May-88	MEL	SUNNY70	22.00	801.00
84	D25	17-May-88	RAY	RAIN	16.00	664.00
85	E70	24-May-88	MEL	SUNNY	23.40	1432.53
86	D07	04-Jun-88	RAY	FAIR	22.50	1087.23
87	D25	06-Jun-88	MIKE	SUNNY85	13.90	793.51
88	D08	14-Jun-88	MEL	SUNNY90	23.50	1171.82
89	D27	18-Jun-88	RAY	FAIR	11.10	1538.68
90	D24	22-Jun-88	RAY	FAIR	26.40	1647.63
91	E84	23-Jun-88	MIKE	SUNNY95	14.10	120.00
92	E70	27-Jun-88	RAY	FAIR	23.40	764.67
93	D17	28-Jun-88	MEL	SUNNY	22.00	953.14
94	E84	29-Jun-88	MIKE	SUNNY80	14.10	124.85
95	D26	07-Jul-88	MIKE	SUNNY95	20.80	1183.06
96	E80	09-Jul-88	MIKE	SUNNY	8.80	1055.88
97	D28	12-Jul-88	MIKE	SHOWERS	17.80	540.26
98	D17	18-Jul-88	MIKE	SUNNY90	22.00	865.86
99	C75	25-Jul-88	MEL	SUNNYHOT	.90	569.42
100	E70	01-Aug-88	RAY	FAIR	23.40	1661.40
101	D26	03-Aug-88	MIKE	SUNNY	20.80	1197.62
102	E70	16-Aug-88			23.40	301.78
103	D16	17-Aug-88	MEL	SUNNY	26.80	863.87
104	D24	17-Aug-88	MIKE	SUNNY90	26.40	1327.59
105	D06	19-Aug-88	MEL	SUNNY80	13.30	888.11
106	E95	01-Sep-88	RAY	FAIR	15.80	855.72
107	E54	23-Sep-88	MEL	SUNNY	18.80	627.25
108	E84	26-Sep-88	RAY	FAIR	14.10	2562.79

APPENDIX(Continued)

109	D18	28-Sep-88	MIKE	SUNNY75	17.00	709.82
110	E83	30-Sep-88	MEL	CLOUDY	20.90	692.55
111	D16	19-Oct-88	MIKE	SUNNY60	26.80	1692.53
112	D49	21-Oct-88	MIKE	CLOUDY50	8.80	744.40
113	E84	27-Oct-88	RAY	FAIR	14.10	1299.01
114	D39	29-Oct-88	MEL	SUNNY	8.00	2602.66
115	E85	29-Oct-88	RAY	FAIR	2.20	3110.23
116	E27	31-Oct-88	MEL	SUNNY	25.50	840.86
117	C76	10-Nov-88	RAY		.90	568.85
118	E85	10-Nov-88	MIKE	SHOWERS45	2.20	2221.89
119	D39	12-Nov-88	MIKE	SUNNY55	8.00	884.91
120	E84	16-Nov-88	RAY	RAIN	14.10	514.85
121	D18	19-Nov-88	MEL	CLOUDY	17.00	1505.79
122	D39	19-Nov-88	MIKE	SUNNY50	8.00	1112.93
123	D35	21-Nov-88	MEL	CLOUDY	18.30	293.67
124	E70	30-Nov-88	MIKE	SUNNY45	23.40	255.01
125	E70	01-Dec-88	MEL	PARTLYCLOUDY	23.40	243.34
126	D24	02-Dec-88	MIKE	SUNNY	26.40	1117.81
127	D61	09-Dec-88	MIKE	SUNNY40	27.00	786.47
128	E85	15-Dec-88	RAY	FAIR	2.20	1690.54
129	D32	19-Dec-88	RAY	FAIR	23.10	529.22
130	D73	20-Dec-88			26.40	222.39

APPENDIX(Continued)

TOTAL COST ASPHALT	COST/ TON ASPHALT	TOTAL COST TACK	COST/ TON TACK	TOTAL COST MATERIAL	COST/ TON MATERIAL	LABORER REGULAR HOURS	TOTAL COST LABORER REGULAR HOURS
4744.08	18.00	52.50	.20	4796.58	18.20	56.00	1228.08
37069.50	19.50	0.00	.00	37069.50	19.50	72.00	1578.96
17209.52	21.20	112.50	.14	17322.02	21.34	80.00	1754.40
33709.94	18.43	936.00	.51	34645.94	18.95	184.00	4035.12
16326.08	19.67	0.00	.00	16326.08	19.67	72.00	1578.96
11958.05	20.59	0.00	.00	11958.05	20.59	56.00	1228.08
18457.50	21.69	0.00	.00	18457.50	21.69	72.00	1578.96
10798.46	21.69	0.00	.00	10798.46	21.69	72.00	1578.96
44558.91	21.25	0.00	.00	44558.91	21.25	72.00	1578.96
50604.96	21.25	225.00	.09	50829.96	21.34	72.00	1578.96
22581.50	19.28	0.00	.00	22581.50	19.28	64.00	1403.52
25861.23	18.98	0.00	.00	25861.23	18.98	72.00	1578.96
9658.96	30.65	360.00	1.14	10018.96	31.79	80.00	1754.40
28362.37	21.25	904.50	.68	29266.87	21.93	80.00	1754.40
16933.65	20.25	0.00	.00	16933.65	20.25	80.00	1754.40
37538.89	18.60	835.00	.41	38373.89	19.01	80.00	1754.40
40761.10	17.03	541.50	.23	41302.60	17.26	88.00	1929.84
8353.03	21.69	0.00	.00	8353.03	21.69	52.00	1140.36
29000.25	19.20	0.00	.00	29000.25	19.20	80.00	1754.40
5835.78	20.20	135.00	.47	5970.78	20.67	72.00	1578.96
16525.80	22.50	342.00	.47	16867.80	22.97	72.00	1578.96
21174.32	20.60	0.00	.00	21174.32	20.60	88.00	1929.84
19096.14	19.00	0.00	.00	19096.14	19.00	80.00	1754.40
27736.38	23.21	426.00	.36	28162.38	23.57	80.00	1754.40
28883.53	19.85	844.00	.58	29727.53	20.43	80.00	1754.40
12424.00	25.00	0.00	.00	12424.00	25.00	64.00	1403.52
6981.89	19.68	60.00	.17	7041.89	19.85	64.00	1403.52
20337.20	19.90	0.00	.00	20337.20	19.90	8.00	175.44
26369.40	18.60	1165.50	.82	27534.90	19.42	88.00	1929.84
21430.10	19.00	760.00	.67	22190.10	19.67	72.00	1578.96
26637.50	19.85	903.00	.67	27540.50	20.52	88.00	1929.84
32621.49	19.85	0.00	.00	32621.49	19.85	88.00	1929.84
11164.92	4.11	1066.50	.39	12231.42	4.50	80.00	1754.40
15381.69	20.20	414.00	.54	15795.69	20.74	88.00	1929.84
26394.38	21.33	0.00	.00	26394.38	21.33	72.00	1578.96
16706.54	22.11	0.00	.00	16706.54	22.11	88.00	1929.84
28725.24	18.18	525.00	.33	29250.24	18.51	80.00	1754.40
8152.81	25.04	187.50	.58	8340.31	25.62	72.00	1578.96
13806.86	12.73	583.50	.54	14390.36	13.27	88.00	1929.84
43784.02	18.60	1042.50	.44	44826.52	19.04	80.00	1754.40
35921.00	17.00	1485.00	.70	37406.00	17.70	80.00	1754.40
29368.31	21.43	30.00	.02	29398.31	21.45	64.00	1403.52
27470.48	18.70	393.00	.27	27863.48	18.97	88.00	1929.84
20288.95	19.69	790.50	.77	21079.45	20.46	72.00	1578.96
13235.98	19.36	1492.50	2.18	14728.48	21.55	88.00	1929.84
13253.90	55.00	0.00	.00	13253.90	55.00	88.00	1929.84
38682.67	19.00	0.00	.00	38682.67	19.00	83.00	1820.19
24022.08	18.60	1146.00	.89	25168.08	19.49	88.00	1929.84
7860.83	20.20	0.00	.00	7860.83	20.20	96.00	2105.28
7867.43	20.79	0.00	.00	7867.43	20.79	80.00	1754.40
4427.86	19.50	75.00	.33	4502.86	19.83	56.00	1228.08
10893.08	22.00	165.00	.33	11058.08	22.33	72.00	1578.96
66642.33	21.25	177.00	.06	66819.33	21.31	88.00	1929.84

APPENDIX(Continued)

25731.24	18.60	862.50	.62	26593.74	19.22	88.00	1929.84
15660.40	20.93	163.00	.22	15823.40	21.15	88.00	1929.84
18014.28	19.00	22.50	.02	18036.78	19.02	88.00	1929.84

40948.87	14.59	0.00	.00	40948.87	14.59	196.00	4298.28
3643.73	21.25	0.00	.00	3643.73	21.25	21.00	460.53
29730.33	19.85	0.00	.00	29730.33	19.85	80.00	1754.40
52942.91	23.50	0.00	.00	52942.91	23.50	80.00	1754.40
64625.29	103.00	187.50	.30	64812.79	103.30	110.00	2412.30
15238.23	19.72	351.00	.45	15589.23	20.17	88.00	1929.84
23066.91	17.60	0.00	.00	23066.91	17.60	88.00	1929.84
21577.11	18.60	972.00	.84	22549.11	19.44	72.00	1578.96
16400.38	19.64	0.00	.00	16400.38	19.64	168.00	3684.24
5607.11	18.95	0.00	.00	5607.11	18.95	48.00	1052.64
17565.12	24.24	0.00	.00	17565.12	24.24	72.00	1578.96
29747.44	19.53	112.50	.07	29859.94	19.60	64.00	1403.52
21735.50	20.68	0.00	.00	21735.50	20.68	64.00	1403.52
27168.42	21.08	45.00	.03	27213.42	21.11	80.00	1754.40
39086.99	21.19	435.00	.24	39521.99	21.42	128.00	2807.04
23613.68	20.76	225.00	.20	23838.68	20.96	160.00	3508.80
56466.00	18.00	1499.99	.48	57965.99	18.48	160.00	3508.80
37018.08	18.00	1137.00	.55	38155.08	18.55	72.00	1578.96
11638.47	19.82	75.00	.13	11713.47	19.94	80.00	1754.40
34434.00	18.00	1183.50	.62	35617.50	18.62	112.00	2456.16
35825.80	21.25	0.00	.00	35825.80	21.25	80.00	1754.40
23617.15	20.01	0.00	.00	23617.15	20.01	80.00	1754.40
29599.12	21.25	1138.50	.82	30737.62	22.07	72.00	1578.96
23410.85	22.17	82.50	.08	23493.35	22.25	80.00	1754.40
14734.32	18.50	0.00	.00	14734.32	18.50	72.00	1578.96
38560.67	21.25	238.50	.13	38799.17	21.38	72.00	1578.96
14733.90	18.39	472.50	.59	15206.40	18.98	80.00	1754.40
13280.00	20.00	0.00	.00	13280.00	20.00	88.00	1929.84
30355.31	21.19	0.00	.00	30355.31	21.19	80.00	1754.40
23582.01	21.69	0.00	.00	23582.01	21.69	72.00	1578.96
17853.97	22.50	0.00	.00	17853.97	22.50	80.00	1754.40
23087.03	19.70	15.00	.01	23102.03	19.71	80.00	1754.40
29234.92	19.00	0.00	.00	29234.92	19.00	80.00	1754.40
35078.04	21.29	0.00	.00	35078.04	21.29	64.00	1403.52
2304.00	19.20	67.50	.56	2371.50	19.76	64.00	1403.52
15828.66	20.70	0.00	.00	15828.66	20.70	72.00	1578.96
23164.81	24.30	1288.50	1.35	24453.31	25.66	88.00	1929.84
2397.12	19.20	52.50	.42	2449.62	19.62	64.00	1403.52
21993.08	18.59	0.00	.00	21993.08	18.59	64.00	1403.52
23757.30	22.50	0.00	.00	23757.30	22.50	80.00	1754.40
11939.74	22.10	0.00	.00	11939.74	22.10	40.00	877.20
14719.62	17.00	1462.50	1.69	16182.12	18.69	64.00	1403.52
13381.37	23.50	468.00	.82	13849.37	24.32	88.00	1929.84
32575.14	19.61	0.00	.00	32575.14	19.61	88.00	1929.84
22670.94	18.93	0.00	.00	22670.94	18.93	72.00	1578.96
6204.59	20.56	0.00	.00	6204.59	20.56	0.00	.00
17450.17	20.20	361.50	.42	17811.67	20.62	80.00	1754.40
27680.25	20.85	60.00	.05	27740.25	20.90	72.00	1578.96
21314.64	24.00	0.00	.00	21314.64	24.00	80.00	1754.40
21914.98	25.61	0.00	.00	21914.98	25.61	88.00	1929.84
11121.14	17.73	0.00	.00	11121.14	17.73	88.00	1929.84
47667.89	18.60	1474.50	.58	49142.39	19.18	88.00	1929.84

APPENDIX(Continued)

14622.29	20.60	303.00	.43	14925.29	21.03	72.00	1578.96
15928.65	23.00	0.00	.00	15928.65	23.00	88.00	1929.84
31619.48	18.68	135.00	.08	31754.48	18.76	80.00	1754.40
14083.19	18.92	157.50	.21	14240.69	19.13	80.00	1754.40
24837.99	19.12	735.00	.57	25572.99	19.69	80.00	1754.40
37972.80	14.59	0.00	.00	37972.80	14.59	183.00	4013.19
59094.37	19.00	0.00	.00	59094.37	19.00	80.00	1754.40
17893.50	21.28	82.50	.10	17976.00	21.38	80.00	1754.40
13367.97	23.50	0.00	.00	13367.97	23.50	80.00	1754.40
42215.91	19.00	0.00	.00	42215.91	19.00	80.00	1754.40

85035.71	96.10	150.00	.17	85185.71	96.26	121.00	2653.53
10219.77	19.85	0.00	.00	10219.77	19.85	72.00	1578.96
31019.26	20.60	654.00	.43	31673.26	21.03	88.00	1929.84
16237.64	14.59	685.50	.62	16923.14	15.21	96.00	2105.28
5388.84	18.35	0.00	.00	5388.84	18.35	59.00	1293.87
5255.75	20.61	244.50	.96	5500.25	21.57	36.00	789.48
4937.36	20.29	0.00	.00	4937.36	20.29	78.00	1710.54
23809.35	21.30	60.00	.05	23869.35	21.35	72.00	1578.96
16476.54	20.95	135.00	.17	16611.54	21.12	80.00	1754.40
32120.26	19.00	0.00	.00	32120.26	19.00	72.00	1578.96
10748.45	20.31	0.00	.00	10748.45	20.31	72.00	1578.96
4025.25	18.10	0.00	.00	4025.25	18.10	48.00	1052.64

APPENDIX(Continued)

COST/ TON LABORER REGULAR HOURS	LABORER OT HOURS	TOTAL COST LABORER OT HOURS	COST/ TON LABORER OT HOURS	TOTAL LABORER HOURS	TOTAL COST LABORER ALL HOURS	COST/ TON LABORER ALL HOURS	OPERATOR REGULAR HOURS
4.66	2.00	38.45	.15	58.00	1266.53	4.81	16.00
.83	15.00	453.66	.24	87.00	2032.62	1.07	24.00
2.16	17.00	554.29	.68	97.00	2308.69	2.84	24.00
2.21	52.50	1667.38	.91	236.50	5702.50	3.12	40.00
1.90	18.00	573.94	.69	90.00	2152.90	2.59	24.00
2.11	2.50	101.01	.17	58.50	1329.09	2.29	24.00
1.86	13.00	432.34	.51	85.00	2011.30	2.36	24.00
3.17	28.50	857.04	1.72	100.50	2436.00	4.89	24.00
.75	18.00	504.72	.24	90.00	2083.68	.99	24.00
.66	34.50	996.92	.42	106.50	2575.88	1.08	24.00
1.20	21.00	702.07	.60	85.00	2105.59	1.80	24.00
1.16	47.00	1405.57	1.03	119.00	2984.53	2.19	24.00
5.57	3.00	77.43	.25	83.00	1831.83	5.81	32.00
1.31	22.00	652.98	.49	102.00	2407.38	1.80	24.00
2.10	44.50	1292.92	1.55	124.50	3047.32	3.64	24.00
.87	33.00	1001.59	.50	113.00	2755.99	1.37	24.00
.81	26.00	769.67	.32	114.00	2699.51	1.13	32.00
2.96	0.00	53.96	.14	52.00	1194.32	3.10	13.00
1.16	28.50	838.04	.55	108.50	2592.44	1.72	24.00
5.47	12.50	472.14	1.63	84.50	2051.10	7.10	24.00
2.15	26.00	883.87	1.20	98.00	2462.83	3.35	24.00
1.88	15.50	457.47	.45	103.50	2387.31	2.32	24.00
1.75	34.50	984.21	.98	114.50	2738.61	2.72	24.00
1.47	36.50	1072.09	.90	116.50	2826.49	2.37	24.00
1.21	31.50	943.24	.65	111.50	2697.64	1.85	24.00
2.82	10.00	318.82	.64	74.00	1722.34	3.47	24.00
3.96	23.00	784.38	2.21	87.00	2187.90	6.17	24.00
.17	109.00	3377.18	3.30	117.00	3552.62	3.48	0.00
1.36	47.00	1406.25	.99	135.00	3336.09	2.35	24.00
1.40	30.50	1017.95	.90	102.50	2596.91	2.30	24.00
1.44	50.50	1512.31	1.13	138.50	3442.15	2.57	24.00
1.17	54.50	1540.51	.94	142.50	3470.35	2.11	24.00
.65	25.00	725.15	.27	105.00	2479.55	.91	48.00
2.53	19.00	569.50	.75	107.00	2499.34	3.28	24.00
1.28	17.00	613.04	.50	89.00	2192.00	1.77	32.00
2.55	45.50	1353.94	1.79	133.50	3283.78	4.35	24.00
1.11	33.50	982.81	.62	113.50	2737.21	1.73	32.00
4.85	10.00	390.81	1.20	82.00	1969.77	6.05	24.00
1.78	39.00	1164.37	1.07	127.00	3094.21	2.85	24.00
.75	36.50	1123.57	.48	116.50	2877.97	1.22	32.00
.83	21.00	620.71	.29	101.00	2375.11	1.12	32.00
1.02	15.50	555.06	.41	79.50	1958.58	1.43	24.00
1.31	27.00	804.93	.55	115.00	2734.77	1.86	40.00
1.53	6.00	271.67	.26	78.00	1850.63	1.80	24.00
2.82	31.00	932.07	1.36	119.00	2861.91	4.19	24.00
8.01	39.00	1153.05	4.78	127.00	3082.89	12.79	24.00
.89	47.00	1509.98	.74	130.00	3330.17	1.64	24.00
1.49	31.50	915.09	.71	119.50	2844.93	2.20	24.00
5.41	17.00	541.33	1.39	113.00	2646.61	6.80	24.00
4.64	15.50	456.03	1.21	95.50	2210.43	5.84	32.00
5.41	8.50	333.73	1.47	64.50	1561.81	6.88	16.00
3.19	13.00	482.94	.98	85.00	2061.90	4.16	24.00
.62	34.00	1007.43	.32	122.00	2937.27	.94	48.00

APPENDIX(Continued)

1.39	29.00	832.60	.60	117.00	2762.44	2.00	40.00
2.58	20.50	608.17	.81	108.50	2538.01	3.39	24.00
2.04	6.50	295.35	.31	94.50	2225.19	2.35	24.00

1.53	57.50	1724.72	.61	253.50	6023.00	2.15	40.00
2.69	11.50	340.99	1.99	32.50	801.52	4.67	8.00
1.17	29.50	907.01	.61	109.50	2661.41	1.78	32.00
.78	32.00	982.83	.44	112.00	2737.23	1.21	32.00
3.84	26.00	975.81	1.56	136.00	3388.11	5.40	24.00
2.50	20.50	608.17	.79	108.50	2538.01	3.28	24.00
1.47	21.50	634.33	.48	109.50	2564.17	1.96	24.00
1.36	21.00	607.33	.52	93.00	2186.29	1.88	32.00
4.41	49.50	1586.45	1.90	217.50	5270.69	6.31	48.00
3.56	0.00	8.48	.03	48.00	1061.12	3.59	24.00
2.18	13.50	390.70	.54	85.50	1969.66	2.72	24.00
.92	13.00	421.28	.28	77.00	1824.80	1.20	24.00
1.34	9.50	279.76	.27	73.50	1683.28	1.60	24.00
1.36	17.00	551.44	.43	97.00	2305.84	1.79	24.00
1.52	24.50	775.26	.42	152.50	3582.30	1.94	48.00
3.09	28.50	917.49	.81	188.50	4426.29	3.89	48.00
1.12	54.50	1693.61	.54	214.50	5202.41	1.66	48.00
.77	15.50	498.54	.24	87.50	2077.50	1.01	32.00
2.99	13.50	448.18	.76	93.50	2202.58	3.75	24.00
1.28	24.50	784.21	.41	136.50	3240.37	1.69	32.00
1.04	13.00	1379.78	.82	93.00	3134.18	1.86	24.00
1.49	21.00	604.21	.51	101.00	2358.61	2.00	24.00
1.13	21.00	634.16	.46	93.00	2213.12	1.59	24.00
1.66	16.00	507.06	.48	96.00	2261.46	2.14	24.00
1.98	7.00	181.81	.23	79.00	1760.77	2.21	24.00
.87	22.00	658.42	.36	94.00	2237.38	1.23	24.00
2.19	24.00	686.19	.86	104.00	2440.59	3.05	32.00
2.91	3.00	93.04	.14	91.00	2022.88	3.05	24.00
1.22	27.00	775.47	.54	107.00	2529.87	1.77	24.00
1.45	14.00	400.28	.37	86.00	1979.24	1.82	24.00
2.21	9.00	340.26	.43	89.00	2094.66	2.64	16.00
1.50	16.00	499.07	.43	96.00	2253.47	1.92	24.00
1.14	33.50	944.82	.61	113.50	2699.22	1.75	24.00
.85	17.00	599.27	.36	81.00	2002.79	1.22	32.00
11.70	17.00	599.27	4.99	81.00	2002.79	16.69	16.00
2.06	35.50	1037.52	1.36	107.50	2616.48	3.42	24.00
2.02	23.00	681.24	.71	111.00	2611.08	2.74	48.00
11.24	11.00	418.71	3.35	75.00	1822.23	14.60	16.00
1.19	21.00	726.66	.61	85.00	2130.18	1.80	24.00
1.66	28.00	818.13	.77	108.00	2572.53	2.44	24.00
1.62	7.00	257.32	.48	47.00	1134.52	2.10	15.00
1.62	8.00	317.48	.37	72.00	1721.00	1.99	24.00
3.39	19.00	574.05	1.01	107.00	2503.89	4.40	32.00
1.16	61.50	1775.92	1.07	149.50	3705.76	2.23	24.00
1.32	20.50	716.39	.60	92.50	2295.35	1.92	24.00
.00	20.50	633.96	2.10	20.50	633.96	2.10	0.00
2.03	26.50	785.39	.91	106.50	2539.79	2.94	24.00
1.19	14.50	540.65	.41	86.50	2119.61	1.60	32.00
1.98	23.00	668.81	.75	103.00	2423.21	2.73	24.00
2.26	36.00	1079.59	1.26	124.00	3009.43	3.52	24.00
3.08	20.00	574.98	.92	108.00	2504.82	3.99	24.00
.75	29.50	860.60	.34	117.50	2790.44	1.09	24.00

APPENDIX(Continued)

2.22	15.00	540.66	.76	87.00	2119.62	2.99	24.00
2.79	12.50	368.19	.53	100.50	2298.03	3.32	24.00
1.04	31.00	1042.51	.62	111.00	2796.91	1.65	24.00
2.36	1.00	116.38	.16	81.00	1870.78	2.51	24.00
1.35	32.00	982.83	.76	112.00	2737.23	2.11	32.00
1.54	72.00	2228.54	.86	255.00	6241.73	2.40	48.00
.56	31.50	968.85	.31	111.50	2723.25	.88	32.00
2.09	19.00	585.66	.70	99.00	2340.06	2.78	24.00
3.08	31.00	947.57	1.67	111.00	2701.97	4.75	32.00
.79	26.50	908.44	.41	106.50	2662.84	1.20	24.00

3.00	29.00	1200.98	1.36	150.00	3854.51	4.36	24.00
3.07	23.50	683.58	1.33	95.50	2262.54	4.39	32.00
1.28	33.00	974.92	.65	121.00	2904.76	1.93	24.00
1.89	35.50	1214.90	1.09	131.50	3320.18	2.98	24.00
4.41	10.50	318.04	1.08	69.50	1611.91	5.49	18.00
3.10	14.00	472.65	1.85	50.00	1262.13	4.95	12.00
7.03	15.00	438.70	1.80	93.00	2149.24	8.83	22.00
1.41	12.00	452.23	.40	84.00	2031.19	1.82	32.00
2.23	1.00	116.38	.15	81.00	1870.78	2.38	32.00
.93	16.00	431.22	.26	88.00	2010.18	1.19	24.00
2.98	15.50	409.47	.77	87.50	1988.43	3.76	24.00
4.73	0.00	8.48	.04	48.00	1061.12	4.77	24.00

APPENDIX(Continued)

TOTAL COST OPERATOR REGULAR HOURS	COST/ TON OPERATOR REGULAR HOURS	OPERATOR OT HOURS	TOTAL COST OPERATOR OT HOURS	COST/ TON OPERATOR OT HOURS	TOTAL OPERATOR HOURS	TOTAL COST OPERATOR ALL HOURS
519.68	1.97	0.00	.00	.00	16.00	519.68
779.52	.41	6.00	264.72	.14	30.00	1044.24
779.52	.96	8.50	379.82	.47	32.50	1159.34
1299.20	.71	15.50	694.42	.38	55.50	1993.62
779.52	.94	10.00	448.88	.54	34.00	1228.40
779.52	1.34	0.00	.00	.00	24.00	779.52
779.52	.92	10.00	448.88	.53	34.00	1228.40
779.52	1.57	11.00	494.92	.99	35.00	1274.44
779.52	.37	5.00	218.68	.10	29.00	998.20
779.52	.33	13.50	610.02	.26	37.50	1389.54
779.52	.67	13.50	610.02	.52	37.50	1389.54
779.52	.57	19.00	863.24	.63	43.00	1642.76
1039.36	3.30	0.00	.00	.00	32.00	1039.36
779.52	.58	9.00	402.84	.30	33.00	1182.36
779.52	.93	13.50	610.02	.73	37.50	1389.54
779.52	.39	14.00	633.04	.31	38.00	1412.56
1039.36	.43	12.00	537.12	.22	44.00	1576.48
422.24	1.10	0.00	.00	.00	13.00	422.24
779.52	.52	12.00	540.96	.36	36.00	1320.48
779.52	2.70	4.00	172.64	.60	28.00	952.16
779.52	1.06	9.00	402.84	.55	33.00	1182.36
779.52	.76	4.50	195.66	.19	28.50	975.18
779.52	.78	13.00	587.00	.58	37.00	1366.52
779.52	.65	13.50	676.40	.57	37.50	1455.92
779.52	.54	11.00	555.68	.38	35.00	1335.20
779.52	1.57	4.00	217.64	.44	28.00	997.16
779.52	2.20	9.50	483.24	1.36	33.50	1262.76
.00	.00	38.00	1835.02	1.80	38.00	1835.02
779.52	.55	16.00	797.12	.56	40.00	1576.64
779.52	.69	11.50	579.82	.51	35.50	1359.34
779.52	.58	17.50	869.56	.65	41.50	1649.08
779.52	.47	17.00	845.41	.51	41.00	1624.93
1559.04	.57	17.00	869.89	.32	65.00	2428.93
779.52	1.02	7.50	386.66	.51	31.50	1166.18
1039.36	.84	9.50	491.40	.40	41.50	1530.76
779.52	1.03	16.50	821.27	1.09	40.50	1600.79
1039.36	.66	16.00	805.28	.51	48.00	1844.64
779.52	2.39	4.00	217.64	.67	28.00	997.16
779.52	.72	16.00	797.13	.73	40.00	1576.65
1039.36	.44	14.50	732.85	.31	46.50	1772.21
1039.36	.49	12.00	612.12	.29	44.00	1651.48
779.52	.57	8.00	410.81	.30	32.00	1190.33
1299.20	.88	11.00	572.00	.39	51.00	1871.20
779.52	.76	3.00	169.35	.16	27.00	948.87
779.52	1.14	11.50	579.82	.85	35.50	1359.34
779.52	3.23	12.00	603.96	2.51	36.00	1383.48
779.52	.38	17.50	869.56	.43	41.50	1649.08
779.52	.60	12.00	603.97	.47	36.00	1383.49
779.52	2.00	4.50	241.79	.62	28.50	1021.31
1039.36	2.75	4.50	249.95	.66	36.50	1289.31
519.68	2.29	0.00	16.32	.07	16.00	536.00

779.52	1.57	7.00	362.51	.73	31.00	1142.03
1559.04	.50	21.00	1063.05	.34	69.00	2622.09
1299.20	.94	17.50	885.88	.64	57.50	2185.08
779.52	1.04	7.50	386.66	.52	31.50	1166.18
779.52	.82	5.00	265.93	.28	29.00	1045.45
1299.20	.46	18.00	910.02	.32	58.00	2209.22
259.84	1.52	8.00	394.48	2.30	16.00	654.32
1039.36	.69	15.00	757.00	.51	47.00	1796.36
1039.36	.46	17.00	853.57	.38	49.00	1892.93
779.52	1.24	7.00	362.51	.58	31.00	1142.03
779.52	1.01	8.00	410.80	.53	32.00	1190.32
779.52	.59	6.00	314.22	.24	30.00	1093.74
1039.36	.90	12.50	636.27	.55	44.50	1675.63
1559.04	1.87	18.00	918.18	1.10	66.00	2477.22
779.52	2.63	0.00	.00	.00	24.00	779.52
779.52	1.08	5.50	241.70	.33	29.50	1021.22
779.52	.51	8.00	356.80	.23	32.00	1136.32
779.52	.74	6.00	264.72	.25	30.00	1044.24
779.52	.60	9.00	402.84	.31	33.00	1182.36
1559.04	.85	16.50	736.62	.40	64.50	2295.66
1559.04	1.37	13.00	575.48	.51	61.00	2134.52
1559.04	.50	21.50	966.82	.31	69.50	2525.86
1039.36	.51	8.00	352.96	.17	40.00	1392.32
779.52	1.33	5.50	241.70	.41	29.50	1021.22
1039.36	.54	10.00	445.04	.23	42.00	1484.40
779.52	.46	6.00	264.72	.16	30.00	1044.24
779.52	.66	6.00	264.72	.22	30.00	1044.24
779.52	.56	10.00	448.88	.32	34.00	1228.40
779.52	.74	6.00	264.72	.25	30.00	1044.24
779.52	.98	4.00	172.64	.22	28.00	952.16
779.52	.43	9.00	402.84	.22	33.00	1182.36
1039.36	1.30	7.50	329.94	.41	39.50	1369.30
768.00	1.16	3.00	138.12	.21	27.00	906.12
768.00	.54	10.00	460.40	.32	34.00	1228.40
768.00	.71	7.50	345.30	.32	31.50	1113.30
512.00	.65	6.00	276.24	.35	22.00	788.24
768.00	.66	6.00	276.24	.24	30.00	1044.24
768.00	.50	14.50	667.58	.43	38.50	1435.58
1024.00	.62	10.50	483.42	.29	42.50	1507.42
519.68	4.33	2.00	84.40	.70	18.00	604.08
779.52	1.02	14.00	633.04	.83	38.00	1412.56
1559.04	1.64	14.50	644.54	.68	62.50	2203.58
519.68	4.16	3.50	153.46	1.23	19.50	673.14
768.00	.65	7.50	398.10	.34	31.50	1166.10
768.00	.73	12.00	615.48	.58	36.00	1383.48
480.00	.89	3.00	167.37	.31	18.00	647.37
779.52	.90	3.00	169.35	.20	27.00	948.87
1039.36	1.83	12.00	612.12	1.07	44.00	1651.48
768.00	.46	21.50	1074.24	.65	45.50	1842.24
768.00	.64	6.50	349.89	.29	30.50	1117.89
.00	.00	6.50	313.89	1.04	6.50	313.89
779.52	.90	9.00	459.09	.53	33.00	1238.61
1039.36	.78	9.50	491.40	.37	41.50	1530.76
768.00	.86	7.50	398.18	.45	31.50	1166.18
779.52	.91	13.50	676.40	.79	37.50	1455.92
768.00	1.22	9.00	470.62	.75	33.00	1238.62
779.52	.30	10.00	507.38	.20	34.00	1286.90
779.52	1.10	6.00	314.23	.44	30.00	1093.75
768.00	1.11	8.00	422.32	.61	32.00	1190.32

APPENDIX(Continued)

779.52	.46	10.50	531.53	.31	34.50	1311.05
768.00	1.03	0.00	36.00	.05	24.00	804.00
1039.36	.80	17.00	853.57	.66	49.00	1892.93
1559.04	.60	25.00	1256.21	.48	73.00	2815.25
1024.00	.33	17.50	893.08	.29	49.50	1917.08
779.52	.93	6.00	314.22	.37	30.00	1093.74
1039.36	1.83	16.50	829.43	1.46	48.50	1868.79
779.52	.35	7.50	386.66	.17	31.50	1166.18

779.52	.88	6.00	314.22	.36	30.00	1093.74
1039.36	2.02	13.00	660.41	1.28	45.00	1699.77
779.52	.52	12.00	603.96	.40	36.00	1383.48
779.52	.70	9.00	459.09	.41	33.00	1238.61
584.64	1.99	3.00	163.24	.56	21.00	747.88
389.76	1.53	5.50	277.84	1.09	17.50	667.60
714.56	2.94	4.50	239.75	.99	26.50	954.31
1039.36	.93	8.00	418.96	.37	40.00	1458.32
1039.36	1.32	0.00	32.64	.04	32.00	1072.00
779.52	.46	6.50	338.37	.20	30.50	1117.89
779.52	1.47	6.50	338.37	.64	30.50	1117.89
779.52	3.51	0.00	.00	.00	24.00	779.52

APPENDIX(Continued)

COST/ TON OPERATOR ALL HOURS	TOTAL LABOR REGULAR HOURS	TOTAL LABOR OT HOURS	TOTAL LABOR HOURS	TOTAL COST LABOR	COST/ TON LABOR	EQUIP. HOURS	TOTAL COST EQUIP.
1.97	72.00	2.00	74.00	1786.21	6.78	16.00	791.50
.55	96.00	21.00	117.00	3076.86	1.62	30.00	1107.50
1.43	104.00	25.50	129.50	3468.03	4.27	32.50	1220.75
1.09	224.00	68.00	292.00	7696.12	4.21	55.50	2097.50
1.48	96.00	28.00	124.00	3381.30	4.07	34.00	1296.50
1.34	80.00	2.50	82.50	2108.61	3.63	24.00	536.25
1.44	96.00	23.00	119.00	3239.70	3.81	34.00	1296.50
2.56	96.00	39.50	135.50	3710.44	7.45	35.00	1207.75
.48	96.00	23.00	119.00	3081.88	1.47	29.00	1136.25
.58	96.00	48.00	144.00	3965.42	1.67	37.50	1387.25
1.19	88.00	34.50	122.50	3495.13	2.98	37.50	1247.50
1.21	96.00	66.00	162.00	4627.29	3.40	43.00	1267.00
3.30	112.00	3.00	115.00	2871.19	9.11	32.00	1128.00
.89	104.00	31.00	135.00	3589.74	2.69	33.00	1247.50
1.66	104.00	58.00	162.00	4436.86	5.31	37.50	1226.50
.70	104.00	47.00	151.00	4168.55	2.07	38.00	1365.00
.66	120.00	38.00	158.00	4275.99	1.79	44.00	1808.00
1.10	65.00	.00	65.00	1616.56	4.20	13.00	601.25
.87	104.00	40.50	144.50	3912.92	2.59	36.00	1288.75
3.30	96.00	16.50	112.50	3003.26	10.40	28.00	1046.00
1.61	96.00	35.00	131.00	3645.19	4.96	33.00	1204.50
.95	112.00	20.00	132.00	3362.49	3.27	28.50	1103.50
1.36	104.00	47.50	151.50	4105.13	4.08	37.00	1300.25
1.22	104.00	50.00	154.00	4282.41	3.58	37.50	1446.00
.92	104.00	42.50	146.50	4032.84	2.77	35.00	1327.50
2.01	88.00	14.00	102.00	2719.50	5.47	28.00	966.50
3.56	88.00	32.50	120.50	3450.66	9.72	33.50	1159.75
1.80	8.00	147.00	155.00	5387.64	5.27	38.00	1476.50
1.11	112.00	63.00	175.00	4912.73	3.47	40.00	1486.50
1.21	96.00	42.00	138.00	3956.25	3.51	35.50	1186.00
1.23	112.00	68.00	180.00	5091.23	3.79	41.50	1484.00
.99	112.00	71.50	183.50	5095.28	3.10	41.00	1508.00
.89	128.00	42.00	170.00	4908.48	1.81	65.00	2590.25
1.53	112.00	26.50	138.50	3665.52	4.81	31.50	1043.00
1.24	104.00	26.50	130.50	3722.76	3.01	41.50	1366.00
2.12	112.00	62.00	174.00	4884.57	6.46	40.50	1486.00
1.17	112.00	49.50	161.50	4581.85	2.90	48.00	1951.00
3.06	96.00	14.00	110.00	2966.93	9.11	28.00	990.25
1.45	112.00	55.00	167.00	4670.86	4.31	40.00	1412.50
.75	112.00	51.00	163.00	4650.18	1.98	46.50	1490.00
.78	112.00	33.00	145.00	4026.59	1.91	44.00	1822.50
.87	88.00	23.50	111.50	3148.91	2.30	32.00	1196.50
1.27	128.00	38.00	166.00	4605.97	3.14	51.00	1878.00
.92	96.00	9.00	105.00	2799.50	2.72	27.00	1033.00
1.99	112.00	42.50	154.50	4221.25	6.18	35.50	1311.00
5.74	112.00	51.00	163.00	4466.37	18.53	36.00	1311.00
.81	107.00	64.50	171.50	4979.25	2.45	41.50	1472.75
1.07	112.00	43.50	155.50	4228.42	3.27	36.00	1300.75
2.62	120.00	21.50	141.50	3667.92	9.43	28.50	1033.00
3.41	112.00	20.00	132.00	3499.74	9.25	36.50	1021.25
2.36	72.00	8.50	80.50	2097.81	9.24	16.00	802.75
2.31	96.00	20.00	116.00	3203.93	6.47	31.00	1044.50
.84	136.00	55.00	191.00	5559.36	1.77	69.00	2457.75

APPENDIX(Continued)

1.58	128.00	46.50	174.50	4947.52	3.58	57.50	2185.25
1.56	112.00	28.00	140.00	3704.19	4.95	31.50	1156.00
1.10	112.00	11.50	123.50	3270.64	3.45	29.00	1038.00

.79	236.00	75.50	311.50	8232.22	2.93	58.00	2392.00
3.82	29.00	19.50	48.50	1455.84	8.49	16.00	593.50
1.20	112.00	44.50	156.50	4457.77	2.98	47.00	1556.00
.84	112.00	49.00	161.00	4630.16	2.06	49.00	1695.50
1.82	134.00	33.00	167.00	4530.14	7.22	31.00	1174.50
1.54	112.00	28.50	140.50	3728.33	4.82	32.00	1197.50
.83	112.00	27.50	139.50	3657.91	2.79	30.00	1189.50
1.44	104.00	33.50	137.50	3861.92	3.33	44.50	1505.50
2.97	216.00	67.50	283.50	7747.91	9.28	64.00	2443.25
2.63	72.00	.00	72.00	1840.64	6.22	24.00	966.00
1.41	96.00	19.00	115.00	2990.88	4.13	29.50	1097.25
.75	88.00	21.00	109.00	2961.12	1.94	32.00	1227.50
.99	88.00	15.50	103.50	2727.52	2.60	30.00	1107.50
.92	104.00	26.00	130.00	3488.20	2.71	33.00	1234.25
1.24	176.00	41.00	217.00	5877.96	3.19	64.50	2434.50
1.88	208.00	41.50	249.50	6560.81	5.77	61.00	2247.50
.81	208.00	76.00	284.00	7728.27	2.46	69.50	2412.75
.68	104.00	23.50	127.50	3469.82	1.69	40.00	1628.50
1.74	104.00	19.00	123.00	3223.80	5.49	29.50	1119.00
.78	144.00	34.50	178.50	4724.77	2.47	42.00	1766.75
.62	104.00	19.00	123.00	4178.42	2.48	30.00	1139.50
.88	104.00	27.00	131.00	3402.85	2.88	30.00	1129.25
.88	96.00	31.00	127.00	3441.52	2.47	34.00	1277.50
.99	104.00	22.00	126.00	3305.70	3.13	30.00	1151.25
1.20	96.00	11.00	107.00	2712.93	3.41	28.00	1019.75
.65	96.00	31.00	127.00	3419.74	1.88	33.00	1195.00
1.71	112.00	31.50	143.50	3809.89	4.76	39.50	1025.00
1.36	112.00	6.00	118.00	2929.00	4.41	27.00	509.25
.86	104.00	37.00	141.00	3758.27	2.62	34.00	1200.00
1.02	96.00	21.50	117.50	3092.54	2.84	31.50	1166.00
.99	96.00	15.00	111.00	2882.90	3.63	22.00	953.00
.89	104.00	22.00	126.00	3297.71	2.81	30.00	1132.00
.93	104.00	48.00	152.00	4134.80	2.69	37.50	1459.25
.91	96.00	27.50	123.50	3510.21	2.13	42.50	1473.50
5.03	80.00	19.00	99.00	2606.87	21.72	18.00	814.00
1.85	96.00	49.50	145.50	4029.04	5.27	38.00	1316.00
2.31	136.00	37.50	173.50	4814.66	5.05	62.50	1989.50
5.39	80.00	14.50	94.50	2495.37	19.99	19.50	809.25
.99	88.00	28.50	116.50	3296.28	2.79	31.50	1208.00
1.31	104.00	40.00	144.00	3956.01	3.75	36.00	1319.25
1.20	55.00	10.00	65.00	1781.89	3.30	18.00	628.75
1.10	88.00	11.00	99.00	2669.87	3.08	27.00	1005.00
2.90	120.00	31.00	151.00	4155.37	7.30	44.00	1280.00
1.11	112.00	83.00	195.00	5548.00	3.34	45.50	1225.25
.93	96.00	27.00	123.00	3413.24	2.85	30.50	1151.25
1.04	.00	27.00	27.00	947.85	3.14	6.50	298.25
1.43	104.00	35.50	139.50	3778.40	4.37	33.00	1181.00
1.15	104.00	24.00	128.00	3650.37	2.75	41.50	1207.50
1.31	104.00	30.50	134.50	3589.39	4.04	31.50	968.50
1.70	112.00	49.50	161.50	4465.35	5.22	37.50	1451.00
1.97	112.00	29.00	141.00	3743.44	5.97	33.00	1174.25
.50	112.00	39.50	151.50	4077.34	1.59	34.00	1311.00

APPENDIX(Continued)

1.54	96.00	21.00	117.00	3213.37	4.53	30.00	1039.75
1.72	112.00	20.50	132.50	3488.35	5.04	32.00	1163.00
.77	104.00	41.50	145.50	4107.96	2.43	34.50	1333.25
1.08	104.00	1.00	105.00	2674.78	3.59	24.00	987.75
1.46	112.00	49.00	161.00	4630.16	3.56	49.00	1721.75
1.08	231.00	97.00	328.00	9056.98	3.48	73.00	2694.00
.62	112.00	49.00	161.00	4640.33	1.49	49.50	1703.50
1.30	104.00	25.00	129.00	3433.80	4.08	30.00	1146.00
3.29	112.00	47.50	159.50	4570.76	8.04	48.50	1639.00
.52	104.00	34.00	138.00	3829.02	1.72	31.50	1174.50

1.24	145.00	35.00	180.00	4948.25	5.59	30.00	1174.50
3.30	104.00	36.50	140.50	3962.31	7.70	45.00	1531.00
.92	112.00	45.00	157.00	4288.24	2.85	36.00	1304.50
1.11	120.00	44.50	164.50	4558.79	4.10	33.00	1260.50
2.55	77.00	13.50	90.50	2359.79	8.04	21.00	728.50
2.62	48.00	19.50	67.50	1929.73	7.57	17.50	602.00
3.92	100.00	19.50	119.50	3103.55	12.75	26.50	891.50
1.30	104.00	20.00	124.00	3489.51	3.12	40.00	1295.50
1.36	112.00	1.00	113.00	2942.78	3.74	32.00	826.50
.66	96.00	22.50	118.50	3128.07	1.85	30.50	1166.75
2.11	96.00	22.00	118.00	3106.32	5.87	30.50	1147.50
3.51	72.00	.00	72.00	1840.64	8.28	24.00	966.00

APPENDIX(Continued)

COST/ TON EQUIP.	TOTAL TRUCKING HOURS	TOTAL COST TRUCKING	COST/ TON TRUCKING	TOTAL VARIABLE COST	TOTAL V.COST/ TON	TOTAL OVER-HEAD
3.00	24.6	1228.19	4.66	8602.48	32.64	678.23
.58	91.2	4562.40	2.40	45816.26	24.10	4891.93
1.50	58.4	2922.37	3.60	24933.17	30.71	2088.96
1.15	157.3	7862.94	4.30	52302.50	28.60	4705.59
1.56	61.6	3079.86	3.71	24083.74	29.01	2136.26
.92	41.9	2096.58	3.61	16699.49	28.75	1494.52
1.52	64.8	3242.31	3.81	26236.01	30.83	2189.92
2.43	35.4	1767.62	3.55	17484.27	35.11	1281.32
.54	110.3	5514.82	2.63	54291.86	25.89	5396.02
.58	114.3	5715.38	2.40	61898.01	25.99	6128.19
1.07	100.9	5047.01	4.31	32371.14	27.64	3013.38
.93	98.1	4904.28	3.60	36659.80	26.91	3505.67
3.58	36.1	1802.77	5.72	15820.92	50.20	811.04
.93	61.1	3056.46	2.29	37160.57	27.84	3434.64
1.47	84.5	4222.96	5.05	26819.97	32.07	2151.91
.68	112.2	5610.65	2.78	49518.09	24.54	5193.57
.76	172.8	8638.01	3.61	56024.60	23.41	6157.50
1.56	38.6	1929.40	5.01	12500.24	32.46	991.02
.85	105.4	5271.40	3.49	39473.32	26.13	3886.85
3.62	32.7	1635.17	5.66	11655.21	40.34	743.44
1.64	66.3	3312.50	4.51	25029.99	34.08	1890.07
1.07	72.2	3607.86	3.51	29248.17	28.45	2645.09
1.29	72.4	3618.22	3.60	28119.74	27.98	2586.36
1.21	54.7	2736.25	2.29	36627.04	30.65	3074.81
.91	88.5	4423.47	3.04	39511.34	27.15	3744.45
1.94	39.3	1962.99	3.95	18072.99	36.37	1278.85
3.27	35.7	1784.85	5.03	13437.15	37.87	913.13
1.44	86.9	4343.37	4.25	31544.71	30.87	2629.88
1.05	153.4	7669.81	5.41	41603.94	29.35	3648.25
1.05	116.6	5831.24	5.17	33163.59	29.40	2902.47
1.11	80.2	4012.40	2.99	38128.13	28.41	3453.27
.92	89.7	4486.48	2.73	43711.25	26.60	4229.03
.95	313.1	15654.64	5.76	35384.79	13.02	6993.88
1.37	62.9	3144.87	4.13	23649.08	31.06	1959.52
1.10	104.4	5221.95	4.22	36705.09	29.66	3184.33
1.97	90.5	4525.98	5.99	27603.09	36.53	1944.39
1.23	122.6	6130.63	3.88	41913.72	26.53	4066.04
3.04	33.7	1686.35	5.18	13983.84	42.95	837.75
1.30	102.2	5108.28	4.71	25582.00	23.59	2790.95
.63	127.6	6379.29	2.71	57345.99	24.36	6057.60
.86	163.5	8177.31	3.87	51432.40	24.34	5437.47
.87	112.9	5646.17	4.12	39389.89	28.74	3526.59
1.28	122.8	6140.46	4.18	40487.91	27.56	3780.27
1.00	123.6	6181.20	6.00	31093.15	30.18	2651.06
1.92	72.3	3615.77	5.29	23876.50	34.93	1758.91
5.44	35.9	1792.89	7.44	20824.16	86.41	620.12
.72	110.8	5537.73	2.72	50672.40	24.89	5239.15
1.01	88.9	4442.79	3.44	35140.04	27.21	3323.50
2.65	50.0	2502.23	6.43	15063.98	38.71	1001.42
2.70	31.6	1581.46	4.18	13969.88	36.92	973.60
3.54	24.7	1235.26	5.44	8638.68	38.04	584.33
2.11	51.0	2549.97	5.15	17856.48	36.06	1274.17

APPENDIX(Continued)

.78	137.4	6868.08	2.19	81704.52	26.05	8070.29
1.58	206.7	10334.00	7.47	44060.51	31.85	3559.96
1.55	60.6	3030.25	4.05	23713.84	31.69	1925.40
1.09	62.6	3128.80	3.30	25474.22	26.87	2439.84
.85	161.7	8083.12	2.88	59656.21	21.26	7222.45
3.46	13.6	679.02	3.96	6372.09	37.16	441.25
1.04	97.4	4867.69	3.25	40611.79	27.12	3854.22
.75	111.3	5564.64	2.47	64833.21	28.78	5797.46
1.87	66.3	3312.83	5.28	73830.26	117.67	1614.59
1.55	80.4	4018.20	5.20	24533.26	31.75	1988.50
.91	112.2	5609.45	4.28	33523.77	25.58	3372.68
1.30	94.2	4709.84	4.06	32626.37	28.12	2985.23
2.93	86.8	4342.31	5.20	30933.85	37.04	2148.90
3.26	17.3	864.00	2.92	9277.75	31.36	761.43
1.51	66.2	3312.15	4.57	24965.40	34.45	1865.06
.81	112.1	5605.78	3.68	39654.34	26.03	3920.00
1.05	59.5	2974.33	2.83	28544.85	27.16	2704.58
.96	90.7	4537.28	3.52	36473.15	28.30	3317.04
1.32	130.6	6530.63	3.54	54365.08	29.47	4747.33
1.98	105.8	5287.93	4.65	37934.92	33.36	2926.38
.77	235.3	11763.75	3.75	79870.76	25.46	8072.58
.79	154.2	7712.10	3.75	50965.50	24.78	5292.23
1.91	52.7	2637.16	4.49	18693.43	31.83	1511.43
.92	146.5	7326.79	3.83	49435.81	25.84	4922.81
.68	69.5	3473.00	2.06	44616.72	26.46	4338.45
.96	85.2	4259.94	3.61	32409.19	27.46	3036.65
.92	62.4	3120.10	2.24	38576.74	27.70	3584.41
1.09	89.3	4466.75	4.23	32417.05	30.70	2717.37
1.28	70.1	3504.38	4.40	21971.38	27.59	2049.54
.66	81.3	4064.75	2.24	47478.66	26.16	4669.64
1.28	78.0	3900.87	4.87	23942.16	29.89	2061.25
.77	45.7	2284.16	3.44	19002.41	28.62	1708.70
.84	103.4	5171.43	3.61	40485.01	28.26	3686.39
1.07	87.0	4348.92	4.00	32189.47	29.61	2797.82
1.20	70.1	3507.31	4.42	25197.18	31.75	2041.97
.97	97.0	4851.33	4.14	32383.07	27.63	3015.50
.95	84.9	4246.76	2.76	39075.73	25.40	3959.55
.89	140.4	7018.90	4.26	47080.65	28.57	4239.92
6.78	11.1	555.60	4.63	6347.97	52.90	308.80
1.72	62.7	3135.15	4.10	24308.85	31.79	1967.76
2.09	76.4	3822.09	4.01	35079.56	36.80	2452.76
6.48	8.8	439.47	3.52	6193.71	49.61	321.28
1.02	116.6	5832.49	4.93	32329.85	27.33	3044.42
1.25	67.2	3357.70	3.18	32390.26	30.68	2717.14
1.16	54.2	2712.11	5.02	17062.49	31.58	1390.27
1.16	71.9	3593.32	4.15	23450.31	27.08	2228.16
2.25	30.2	1508.96	2.65	20793.70	36.52	1465.31
.74	126.3	6313.32	3.80	45661.71	27.48	4275.35
.96	82.4	4119.81	3.44	31355.24	26.18	3081.89
.99	25.6	1279.55	4.24	8730.24	28.93	776.58
1.37	96.4	4820.39	5.58	27591.46	31.94	2223.03
.91	124.8	6239.67	4.70	38837.79	29.25	3416.34
1.09	65.4	3268.24	3.68	29140.77	32.81	2285.41
1.70	62.0	3097.71	3.62	30929.04	36.14	2202.06

APPENDIX(Continued)

1.87	61.1	3054.71	4.87	19093.54	30.44	1614.13
.51	133.8	6688.88	2.61	61219.61	23.89	6594.94
1.46	42.3	2115.26	2.98	21293.67	30.00	1826.61
1.68	70.6	3532.01	5.10	24112.01	34.82	1782.17
.79	210.2	10510.61	6.21	47706.30	28.19	4355.46
1.33	39.6	1980.10	2.66	19883.32	26.71	1915.60
1.33	132.5	6624.95	5.10	38549.85	29.68	3342.80
1.04	199.4	9968.19	3.83	59691.97	22.93	6697.54
.55	169.2	8459.83	2.72	73898.03	23.76	8003.69
1.36	76.0	3800.69	4.52	26356.49	31.34	2163.82
2.88	47.6	2377.79	4.18	21955.52	38.60	1463.85
.53	264.8	13242.46	5.96	60461.89	27.21	5717.69

1.33	67.4	3371.51	3.81	94679.97	106.99	2277.18
2.97	62.1	3104.55	6.03	18817.63	36.55	1324.89
.87	138.2	6911.58	4.59	44177.58	29.34	3874.91
1.13	92.2	4607.53	4.14	27349.96	24.57	2863.95
2.48	33.5	1673.92	5.70	10151.05	34.57	755.71
2.36	21.4	1068.49	4.19	9100.47	35.69	656.23
3.66	21.9	1097.46	4.51	10029.87	41.22	626.20
1.16	95.0	4750.69	4.25	33405.05	29.88	2876.51
1.05	66.8	3342.50	4.25	23723.32	30.16	2023.86
.69	89.9	4496.84	2.66	40911.92	24.20	4350.34
2.17	42.2	2111.59	3.99	17113.86	32.34	1361.86
4.34	13.0	649.38	2.92	7481.27	33.64	572.29

APPENDIX(Continued)

OVER-HEAD/ TON	TOTAL COST	TOTAL COST/ TON	TOTAL REVENUE	TOTAL REVENUE/ TON	GROSS PROFIT	GROSS PROFIT/ TON	JOB CLASS
2.57	9280.71	35.21	7762.45	29.45	-1518.26	-5.76	1
2.57	50708.19	26.67	57695.35	30.35	6987.16	3.68	1
2.57	27022.13	33.29	28561.95	35.18	1539.82	1.90	1
2.57	57008.09	31.18	57429.04	31.41	420.95	.23	1
2.57	75444.85	120.24	78428.75	125.00	2983.90	4.76	1
2.57	26521.76	34.32	351.85	.46	-26169.91	-33.87	1
2.57	36896.45	28.15	47117.00	35.95	10220.55	7.80	1
2.57	35611.61	30.70	33150.07	28.58	-2461.54	-2.12	1
2.57	33082.75	39.62	27760.77	33.24	-5321.98	-6.37	1
2.57	10039.18	33.93	9626.10	32.53	-413.08	-1.40	2
2.57	26830.46	37.02	34523.59	47.63	7693.13	10.61	2
2.57	43574.34	28.61	46765.61	30.70	3191.27	2.09	2
2.57	31249.43	29.73	34912.75	33.22	3663.32	3.49	2
2.57	39790.19	30.87	41320.00	32.06	1529.81	1.19	2
2.57	59112.41	32.04	59917.69	32.48	805.28	.44	2
2.57	40861.30	35.93	37670.55	33.13	-3190.75	-2.81	2
2.57	87943.34	28.03	93869.00	29.92	5925.66	1.89	2
2.57	56257.73	27.36	61491.75	29.90	5234.02	2.55	2
2.57	20204.85	34.40	22740.10	38.72	2535.25	4.32	2
2.57	54358.62	28.42	57780.30	30.20	3421.68	1.79	2
2.57	48955.17	29.04	56646.91	33.60	7691.74	4.56	2
2.57	35445.84	30.04	41697.41	35.34	6251.57	5.30	2
2.57	42161.15	30.27	48319.44	34.69	6158.29	4.42	2
2.57	35134.43	33.27	36958.95	35.00	1824.52	1.73	2
2.57	24020.92	30.16	27875.75	35.00	3854.83	4.84	2
2.57	52148.30	28.74	61289.23	33.78	9140.93	5.04	2
2.57	26003.41	32.46	25396.20	31.71	-607.21	-.76	2
2.57	20711.11	31.19	21677.50	32.65	966.39	1.46	2
2.57	44171.40	30.83	46014.90	32.12	1843.50	1.29	2
2.57	34987.29	32.18	47973.40	44.12	12986.11	11.94	2
2.57	27239.16	34.33	23032.80	29.03	-4206.36	-5.30	2
2.57	35398.57	30.21	34361.65	29.32	-1036.92	-.88	2
2.57	43035.28	27.97	46667.25	30.33	3631.97	2.36	2
2.57	51320.57	31.15	55967.13	33.97	4646.56	2.82	2
2.57	6656.77	55.47	7858.50	65.49	1201.73	10.01	2
2.57	26276.61	34.36	24928.24	32.60	-1348.37	-1.76	2
2.57	37532.32	39.38	29688.98	31.15	-7843.34	-8.23	2
2.57	6514.99	52.18	8160.70	65.36	1645.71	13.18	2
2.57	35374.27	29.90	47139.00	39.84	11764.73	9.94	2
2.57	35107.40	33.25	40104.00	37.98	4996.60	4.73	2
2.57	18452.76	34.16	20442.40	37.84	1989.64	3.68	2
2.57	25678.46	29.66	27135.61	31.34	1457.15	1.68	2
2.57	22259.02	39.09	19756.51	34.70	-2502.51	-4.39	2
2.57	49937.06	30.06	52069.90	31.34	2132.84	1.28	2
2.57	34437.13	28.75	48887.00	40.82	14449.87	12.07	2
2.57	9506.82	31.50	9838.02	32.60	331.20	1.10	2
2.57	29814.50	34.51	29805.38	34.50	-9.12	-.01	2
2.57	42254.14	31.83	47619.81	35.87	5365.67	4.04	2
2.57	31426.19	35.39	34500.00	38.85	3073.81	3.46	2
2.57	33131.10	38.72	45353.16	53.00	12222.06	14.28	2
2.57	20707.67	33.01	20379.60	32.49	-328.07	-.52	2
2.57	67814.55	26.46	72651.60	28.35	4837.05	1.89	2
2.57	23120.28	32.57	20979.75	29.56	-2140.53	-3.02	2

APPENDIX(Continued)

2.57	25894.17	37.39	25485.60	36.80	-408.57	-.59	2
2.57	52061.76	30.76	58169.83	34.37	6108.07	3.61	2
2.57	21798.92	29.28	22901.37	30.76	1102.45	1.48	2
2.57	41892.65	32.25	46035.00	35.44	4142.35	3.19	2
2.57	66389.51	25.51	97469.61	37.45	31080.10	11.94	2
2.57	81901.72	26.33	89120.00	28.65	7218.28	2.32	2
2.57	28520.31	33.92	37096.84	44.12	8576.53	10.20	2
2.57	23419.37	41.17	18914.26	33.25	-4505.11	-7.92	2
2.57	66179.58	29.79	65536.00	29.50	-643.58	-.29	2
2.57	26220.00	31.58	29615.15	35.67	3395.15	4.09	1
2.57	18194.01	31.33	19165.41	33.00	971.40	1.67	1
2.57	28425.93	33.40	28046.50	32.96	-379.43	-.45	1
2.57	18765.59	37.69	16192.95	32.52	-2572.64	-5.17	1
2.57	59687.88	28.46	70455.50	33.60	10767.62	5.14	1
2.57	68026.20	28.57	80315.37	33.73	12289.17	5.16	1
2.57	35384.52	30.22	40445.00	34.54	5060.48	4.32	1
2.57	40165.47	29.48	44166.06	32.42	4000.59	2.94	1
2.57	16631.96	52.77	9658.96	30.65	-6973.00	-22.12	1
2.57	40595.21	30.42	46051.92	34.50	5456.71	4.09	1
2.57	28971.88	34.65	31943.98	38.20	2972.10	3.55	1
2.57	54711.66	27.11	56931.52	28.21	2219.86	1.10	1
2.57	62182.09	25.99	70555.60	29.49	8373.51	3.50	1
2.57	13491.26	35.03	18202.00	47.26	4710.74	12.23	1
2.57	43360.18	28.71	52865.05	35.00	9504.87	6.29	1
2.57	12398.65	42.92	9984.60	34.56	-2414.05	-8.36	1
2.57	26920.06	36.65	23198.00	31.58	-3722.06	-5.07	1
2.57	31893.26	31.03	34000.00	33.08	2106.74	2.05	1
2.57	30706.10	30.55	30906.75	30.75	200.65	.20	1
2.57	39701.85	33.23	40715.63	34.08	1013.78	.85	1
2.57	43255.79	29.73	43802.56	30.10	546.77	.38	1
2.57	19351.84	38.94	25398.54	51.11	6046.70	12.17	1
2.57	14350.27	40.44	25340.50	71.41	10990.23	30.97	1
2.57	34174.59	33.44	43094.40	42.17	8919.81	8.73	1
2.57	45252.20	31.92	40493.32	28.56	-4758.88	-3.36	1
2.57	36066.07	31.98	38133.30	33.81	2067.23	1.83	1
2.57	41581.40	30.99	40504.02	30.18	-1077.38	-.80	1
2.57	47940.28	29.17	48644.64	29.60	704.36	.43	1
2.57	42378.68	15.59	83970.81	30.90	41592.13	15.30	1
2.57	25608.60	33.63	26386.78	34.65	778.18	1.02	1
2.57	39889.43	32.24	43186.77	34.90	3297.34	2.66	1
2.57	29547.49	39.11	32511.89	43.03	2964.40	3.92	1
2.57	45979.76	29.10	48067.18	30.42	2087.42	1.32	1
2.57	14821.59	45.53	14172.65	43.53	-648.94	-1.99	1
2.57	28372.94	26.16	21094.27	19.45	-7278.67	-6.71	1
2.57	63403.58	26.93	66461.84	28.23	3058.26	1.30	1
2.57	56869.87	26.91	63580.60	30.09	6710.73	3.18	1
2.57	42916.48	31.32	45701.97	33.35	2785.49	2.03	1
2.57	44268.18	30.13	45302.60	30.84	1034.42	.70	1
2.57	33744.21	32.76	35541.16	34.50	1796.95	1.74	1
2.57	25635.40	37.51	21061.02	30.81	-4574.38	-6.69	1
2.57	21444.29	88.99	18796.44	78.00	-2647.85	-10.99	1
2.57	55911.55	27.46	68689.10	33.74	12777.55	6.28	1
2.57	38463.54	29.78	36961.75	28.62	-1501.79	-1.16	1
2.57	16065.40	41.28	13231.10	34.00	-2834.30	-7.28	1
2.57	14943.48	39.50	15804.04	41.77	860.56	2.27	1
2.57	9223.01	40.62	9576.00	42.17	352.99	1.55	1
2.57	19130.65	38.64	16605.00	33.54	-2525.65	-5.10	1
2.57	89774.81	28.63	104629.65	33.36	14854.84	4.74	1
2.57	47620.47	34.42	39275.19	28.39	-8345.28	-6.03	1

APPENDIX(Continued)

2.57	25639.24	34.27	31754.88	42.44	6115.64	8.17	1
2.57	27914.05	29.44	32338.00	34.11	4423.95	4.67	1
2.57	66878.66	23.83	105108.66	37.45	38230.00	13.62	1
2.57	6813.34	39.73	5701.37	33.25	-1111.97	-6.48	1
2.57	44466.01	29.69	44333.40	29.60	-132.61	-.09	1
2.57	70630.67	31.35	74908.59	33.25	4277.92	1.90	1
2.57	96957.14	109.57	104739.40	118.36	7782.26	8.79	2
2.57	20142.51	39.12	15239.56	29.60	-4902.95	-9.52	2
2.57	48052.49	31.91	55350.50	36.76	7298.01	4.85	2
2.57	30213.91	27.15	41679.22	37.45	11465.31	10.30	2
2.57	10906.76	37.14	9544.27	32.50	-1362.49	-4.64	2
2.57	9756.70	38.26	8592.80	33.70	-1163.90	-4.56	2
2.57	10656.07	43.79	7932.88	32.60	-2723.19	-11.19	2
2.57	36281.56	32.46	37279.98	33.35	998.42	.89	2
2.57	25747.17	32.74	29488.00	37.49	3740.83	4.76	2
2.57	45262.26	26.77	51155.20	30.26	5892.94	3.49	2
2.57	18475.72	34.91	21168.80	40.00	2693.08	5.09	2
2.57	8053.55	36.21	9626.10	43.28	1572.55	7.07	2

APPENDIX(Continued)

PRICE PER TON ASPHALT		
=========		
18.00	19.00	19.00
19.50	18.60	21.29
21.20	20.20	19.20
18.43	20.79	20.70
19.67	19.50	24.30
20.59	22.00	19.20
21.69	21.25	18.59
21.69	18.60	22.50
21.25	20.93	22.10
21.25	19.00	17.00
19.28		23.50
18.98		19.61
30.65		18.93
21.25		20.56
20.25	14.59	20.20
18.60	21.25	20.85
17.03	19.85	24.00
21.69	23.50	25.61
19.20	103.00	17.73
20.20	19.72	18.60
22.50	17.60	20.60
20.60	18.60	23.00
19.00	19.64	18.68
23.21	18.95	18.92
19.85	24.24	19.12
25.00	19.53	14.59
19.68	20.68	19.00
19.90	21.08	21.28
18.60	21.19	23.50
19.00	20.76	19.00
19.85	18.00	
19.85	18.00	
4.11	19.82	
20.20	18.00	
21.33	21.25	96.10
22.11	20.01	19.85
18.18	21.25	20.60
25.04	22.17	14.59
12.73	18.50	18.35
18.60	21.25	20.61
17.00	18.39	20.29
21.43	20.00	21.30
18.70	21.19	20.95
19.69	21.69	19.00
19.36	22.50	20.31
55.00	19.70	18.10

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10. LIST OF FIGURES

Figure Page

1 Criteria for Evaluating Research Problems. From "How Evaluation Guides AI Research" by P. Cohen and A. Howe, 1988. AI Magazine, Winter, p. 36. Copyright 1988 by AI Magazine. Reprinted by permission. 36

2 Criteria for Evaluating Methods. From "How Evaluation Guides AI Research" by P. Cohen and A. Howe, 1988. AI Magazine, Winter, p. 37. Copyright 1988 by AI Magazine. Reprinted by permission 37

3 Criteria for Evaluating Method Implementation. From "How Evaluation Guides AI Research" by P. Cohen and A. Howe, 1988. AI Magazine, Winter, p. 39. Copyright 1988 by AI Magazine. Reprinted by permission. 38

4 Criteria for Evaluating the Experiments' Design. From "How Evaluation Guides AI Research" by P. Cohen and A. Howe, 1988. AI Magazine, Winter, p. 39. Copyright 1988 by AI Magazine. Reprinted by permission. 39

5 Criteria for Evaluating What the Experiments Told Us. From "How Evaluation Guides AI Research" by P. Cohen and A. Howe, 1988. AI Magazine, Winter, p. 41. Copyright 1988 by AI Magazine. Reprinted by permission 40

6 Number of "Bad" Matches vs. Number of Runs: Range: 1 to 989 63

7 Number of "Bad" Matches vs. Number of Runs: Range: 1 to 100 64

8 Number of "Bad" Matches vs. Number of Runs: Range: 101 to 200 65

9 BrainMaker Screen Display: Learning Parameters. 66

10 BrainMaker Screen Display: Test Fact 1. 67

11 BrainMaker Screen Display: Test Fact 2. 68

12 BrainMaker Screen Display: Test Fact 3. 69

13 BrainMaker Screen Display: Test Fact 4. 70

10. LIST OF FIGURES (Continued)

Figure Page

14 BrainMaker Screen Display: Test Fact 5. 71

15 BrainMaker Screen Display: Test Fact 6. 72

16 BrainMaker Screen Display: Test Fact 7. 73

17 BrainMaker Screen Display: Test Fact 8. 74

18 BrainMaker Screen Display: Test Fact 9. 75

19 BrainMaker Screen Display: Test Fact 10 76

20 BrainMaker Screen Display: Test Fact 11 77

21 BrainMaker Screen Display: Test Fact 12 78

22 BrainMaker Screen Display: Test Fact 13 79

23 Neural Network: Calculation of Root Mean Squares for Gross Profits and Gross Profits per Ton. 80

24 Neural Network Graphs of Gross Profits: Observed and Predicted Values. 81

25 Neural Network Graphs of Gross Profits per Ton: Observed and Predicted Values. 82

26 Regression Analysis: Correlation Matrix 98

27 Regression Analysis: Ten-column Matrix. 99

28 Regression Analysis: Beta Calculations. 100

29 Regression Analysis: Residual Calculations. . . 101

30 Regression Analysis Graphs of Gross Profits: Observed, Predicted, and Residual Values 102

31 Regression Analysis Graphs of Gross Profits per Ton: Observed, Predicted, and Residual Values . 103

32 Regression Analysis: Calculation of Root Mean Squares for Gross Profits and for Gross Profits per Ton. 104