NEURAL NETWORK-BASED COST ESTIMATING

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ABSTRACT

NEURAL NETWORK–BASED COST ESTIMATING

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This thesis presents a neural network-based cost estimating method, developed for the generation of conceptual cost estimates for low-rise prefabricated structural steel buildings. Detailed cost estimating is current practice for this type of buildings, since cost estimators are often challenged by a wide variety of different parameters.

The developed method employs neural networks (NNs) for modeling individual project parameters associated with the direct cost of a project. It integrates NN cost models with cost adjustments, allowing for evaluation of different project alternatives, in a timely manner. The ability of NNs to capture real life experiences encountered on actual projects (i.e. actual costs), generalize and utilize that knowledge for estimating the cost of new projects makes it a very powerful tool to the application at hand.

Data used in this study (75 building projects) were collected from a large manufacturer of prefabricated structural steel buildings in Canada (Canam Manac) over a 3-month period. The performance of developed cost models was tested against costs incurred by projects not used in training of those models, and costs predicted by regression. Results indicate that the proposed models,

when used for projects with parameters within the range for which the models were trained, outperform regression. In addition, the proposed models can account for a number of parameters defining a project, and bearing considerable impact on the project cost. The proposed methodology can easily be adapted to provide decision-support for risk management and to assist in developing productivity models in a wide range of industries.

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NOMENCLATURE

AACE:	Association for the Advancement of Cost Engineering
ACE:	Automated Cost Estimating
AI:	Artificial Intelligence
BPNN:	Backpropagation Neural Network
CCE:	Conceptual Cost Estimate
CER:	Cost Estimating Relationship
CA:	Area of Canopy
CL:	Length of Canopy
C.O.:	Change Order
CII:	Construction Industry Institute
Door:	Number of Doors
GRNN:	General Regression Neural Network
H.O.:	Head Office
KBES:	Knowledge Based Expert Systems
LLoad:	Lateral Load
NNs:	Neural Networks
OM:	Order of Magnitude Estimate of Total Project Cost
Opn:	Percentage of Openings as a Function of Wall Area
P&E:	Planning & Engineering
Perim:	Perimeter
PHt:	Panel Height

PS: PARAMETRIC COST STIMATING OF STEEL FRAMING

PW: PARAMETRIC COST ESTIMATING OF WALL PANELS

RFP: REQUEST FOR PROPOSAL

WALL: COST PER FT^2 OF WALL PANELS

WIN: NUMBER OF WINDOWS

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CHAPTER 1- INTRODUCTION

1.1 Cost Estimating Environment

Increased concern about quality assurance, project cost and duration along with traditional site problems related to material storage such as theft, damage and deterioration caused by exposure to rain, snow, sunlight, etc., and other factors such as material waste, and labor related constraints are all driving the construction industry to prefabrication. The prefabrication process, associated to an extensive use of CAD systems, results in consistent, custom designed high quality products, built to federal, state and local code requirements by a stable and skilled workforce in the controlled environment of a factory. This results in lower production costs and reduced project duration.

Prefabrication allows timely return on investment for owners and supports fast-track delivery of constructed facilities. However, production optimization does not ensure a company's survival. In an increasingly competitive market, a company will find leverage in consistently delivering projects optimized to meet well–defined criteria, be it cost, schedule and/or expected performance. A project's optimization can be obtained by experimenting with different design variables, one at a time, at a predesign stage. This is the stage where decisions having the greatest impact on project cost, schedule and performance are made. Clearly, this stage is most crucial for meeting a project's criteria, and front-end cost estimating is vital in the project development. Estimates prepared at this early stage, accordingly, form the basis for analyses of return on investment and, assist owners and their agents in making go-no-go decisions.

This thesis focuses on such cost estimates. Front-end, parametric, conceptual and/or order of magnitude cost estimates refer to, in this thesis, estimates using main parameters of a project to predict its cost. These estimates are used to assist in go-no-go decisions while minimizing estimating efforts spent on non-viable projects (Melin 1994, Paek 1994, Barrie and Paulson 1992, Carr 1989, Karshenas 1984).

However, the generation of conceptual estimates to a reasonable degree of accuracy, in a timely fashion, can be considerably complex. The highly unstructured nature of these estimates, allied to individual estimating experience and different estimating practices, may concur to the generation of inconsistent and therefore unreliable cost estimates. This problem is heightened in the cost estimating of low-rise buildings (see Figure 1). The individual characteristics of these buildings do not favor conceptual estimating. In the process, cost estimators are often challenged by a wide variety of different parameters. Detailed cost estimating, therefore, is currently used in this type of buildings, making estimating a time consuming and costly process.

While this practice is well suited to past market conditions, it has become inadequate for current industry needs (i.e. tough competition, limited resources, etc.). For instance, in case of a project defined by 4 (four) design parameters, the consideration of three different values for each parameter, varying one parameter at a time, would generate 81 (eighty-one) different project alternatives, and, as such, may require the generation of 81 (eighty-one) detailed cost estimates.

The above example illustrates that optimal solutions can not be achieved, in a timely and cost effective manner, through the generation of detailed cost estimates for different scenarios for each received Request For Proposal (RFP). The time and cost involved in preparing such estimates are prohibitive for planning purposes. The result is, in most cases, that project proposals far from optimal are prepared. The goal of defining a project of minimum cost while meeting determined criteria may not simply be achieved. A solution for this problem is, therefore, to automate the cost estimating process, in such a way to allow for 1) an interactive (owner and contractor) project scope definition, 2) the timely generation of what-if type scenarios, 3) reliable cost estimate to assist in go-no-go decisions, and 4) an open and flexible cost estimating environment capable of benefiting from actual costs incurred on previous projects and of accounting for market conditions.

Optimizing the cost estimating process means determining the best tools and system to be used for that end. Realizing that, construction companies are looking for new concepts and advanced tools to assist the optimization of the cost estimating process. As such, automation is looked at as a tool to bring to the process the efficiency and accuracy so needed in delivering a number of alternative cost estimates generated in a timely and cost effective manner. This is expected to provide companies with a competitive edge. The integration of conceptual cost estimating principles with neural networks (NNs) to develop a methodology capable of responding to these needs is discussed in this thesis.

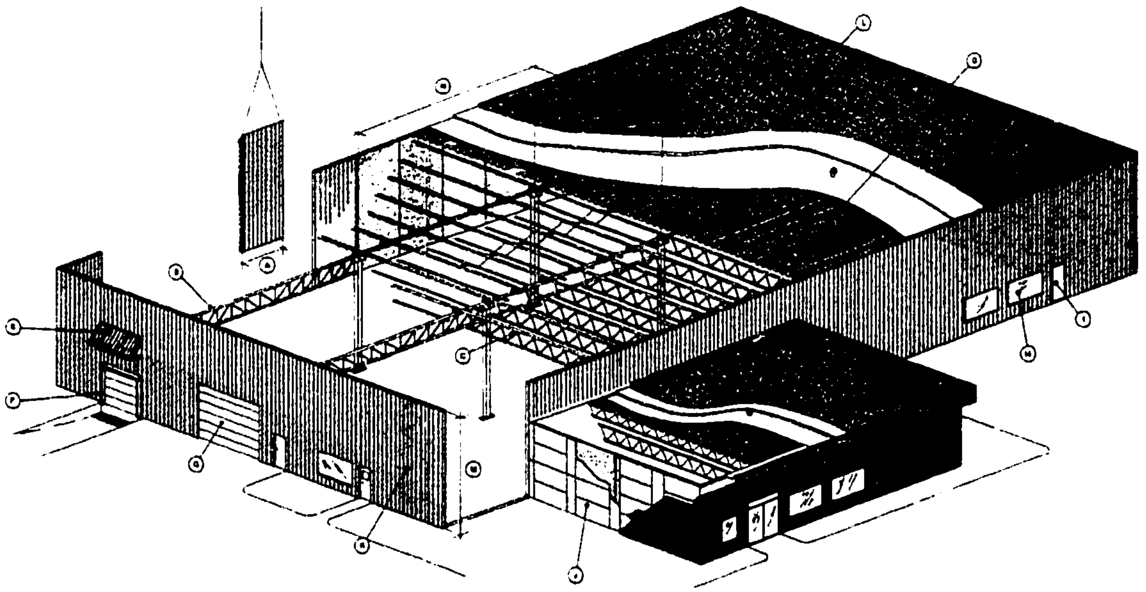

Figure 1 Low-rise Prefabricated Structural Steel Building

The use of NNs in conceptual estimating increases reliability in the process while improving the efficiency in generating the necessary cost information to the decision making process. NNs nearly optimize the estimating process by providing the user with on time cost estimates for a number of project alternatives. NNs provide the cost estimating team with a systematic and efficient approach for studying and evaluating a number of alternatives to determine near optimum configurations of buildings that satisfy owners' construction needs and budgeting constraints. It draws upon the company's experience and domain knowledge in a reasonably accurate and consistent way, rather than individual preconceptions of estimators. As a result, estimating time and cost are considerably reduced.

An Automated Cost Estimating system (ACE) is proposed in an effort to improve the cost estimating process of this class of buildings. ACE is designed to provide the user simple data input facilities for: 1) estimation of direct cost of the project, 2) cost adjustments, 3) allocation of markups to individual cost items and taxes, and 4) the generation of reports. It supports an order of magnitude type estimate, a parametric wall cost estimate and a parametric structure cost estimate.

An order of magnitude estimate will predict the total direct cost of a building shell (i.e. superstructure, exterior closure and roofing). A parametric type estimate (wall and/or structure) allows for cost prediction of building walls (exterior walls, windows, exterior doors and openings) and/or cost prediction of the building's steel framing (including roof coverings and openings). Adjustments for non-standard panels, special wall painting, special structural painting, freight and erection may be incorporated to the direct cost predicted by the neural network models. A spreadsheet is used to calculate these adjustments.

The system's reporting capabilities display project's general information, project's description, direct cost (lump sum and/or cost breakdown), overheads and profits, and the total cost estimate (itemized and/or lump sum) upon request. ACE is limited to the cost estimating of low-rise commercial/industrial structural steel buildings. The utilization of the proposed system is expected to free up estimators time, which will then be put to use in estimating pre-selected projects, found initially acceptable to owners.

1.2 Neural Networks in Cost Estimating

Artificial neural networks try to reproduce the generalization abilities of a human neural system. They learn through training when presented to data sets consisting of inputs associated with output(s) (Creese and Li 1995, Flood and Kartam 1994, Kartam et al 1993, Garret 1992, Moselhi et al. 1991b). Neural networks are, therefore, capable of drawing upon real life experience in an accurate and consistent manner. Principal benefits of using neural network-based cost models include non-reflection of individual preconceptions, the identification of near optimum parameters for lower cost and higher quality solutions, and considerable time and resource savings in the cost estimating process (Moselhi et al 1991b).

Neural networks are of particular advantage when dealing with highly non-linear and complex independent variables, as in the case of cost estimating low-rise structural steel buildings. The ability of these networks to capture the impact of a project's physical characteristics on its cost, generalize and utilize that knowledge for estimating the cost of new projects makes it a very powerful tool to the application at hand. Neural networks exhibit a number of advantages that makes them especially suitable for cost estimating. These include: 1) ability to account for complex cases requiring large number of parameters to be considered in parallel; 2) learning by example, associating inputs to output(s); 3) capturing and benefiting from the experience gained on actual projects, 4) speed of computation; 5) generalization capabilities; and 6) fault tolerance (Flood and Kartam 1994, Kartam et al 1993, Garret et al.1992, Moselhi et al. 1991b).

Neural networks, however, present also shortcomings, they: 1) are not transparent enough to provide explanation facility or reasoning behind the generated solution; 2) are sensitive to the organization and preparation of the data used in training, as well as, to a larger degree, on the configuration of the network itself; and 3) require the availability of a sizable number of training examples that may be difficult to assemble. Different architectures and training rules define different types of neural network. The backpropagation paradigm is most commonly used for the development of civil engineering, and more specifically construction management, applications (Flood and Kartam 1994, Kartam et al 1993, Garret et al.1992, Garret 1992, Moselhi et al. 1991b).

1.3 Scope and Objectives

This thesis focuses primarily on the cost estimating process of low-rise structural-steel commercial and/or industrial buildings. It investigates the development of a methodology for a decision-support system to assist in the cost estimating process of this class of buildings, considering a number of essential variables. Such methodology intends to generate cost estimates, benefiting from current industry practice and domain knowledge through the use of commercial software (spreadsheet and neural networks). This study follows the UNIFORMAT II (Bowen et al. 1992) structure. It focuses on the cost of the building shell, i.e. superstructure (structural steel framing), exterior closure (exterior walls, windows, exterior doors and openings) and roofing. Costs of substructure (foundation and basement construction), interiors (interior construction and finishes), services (conveying systems, plumbing, HVAC, fire protection and electrical), equipment & furnishing, special construction & demolition, and building sitework are not considered in this work. The proposed methodology, however, can be applied to other types of projects, including heavy civil projects, productivity and risk models (Siqueira 1999).

The primary objectives of this research are:

1) Study current cost estimating practice for low-rise structural steel buildings and identify essential parameters involved in this process.
2) Develop a methodology and implement it to efficiently integrate direct cost estimating, cost adjustments, markup allocation and generation of project related reports, capturing current cost estimating practice. The developed methodology is expected to minimize the cost and reduce the time involved in the preparation of project bid proposals, by generating a number of conceptual cost estimates for different project alternatives. The methodology

is intended to reduce estimating effort spent on non-selected projects, which either fail to meet owners construction needs and/or their budgetary constraints.

3) Evaluate the performance of developed system using cost incurred in actual projects.

1.4 Research Methodology

The methodology adopted in this research is based on a field investigation of current cost estimating practice carried out by a major structural steel fabricator in Quebec. It involves a comprehensive study of the actual cost of 75 (seventy-five) projects.

The study includes:

1) Review of project documents and current estimating practice.
2) Extensive literature review focusing on conceptual, order of magnitude type cost estimates and the various tools utilized for these estimates. Special attention was directed towards computer-oriented tools.
3) Based on the findings of the two steps above, development of an efficient and practical cost estimating methodology for low-rise structural-steel buildings.
4) Implementation of the developed methodology in a prototype system utilizing commercial available software systems.
5) Testing the developed system using actual projects in order to validate its accuracy.

1.5 Thesis Organization

Chapter 2 presents a literature review comprising: 1) current cost estimating practice at the company providing the data for this study, 2) cost estimating, and 3) neural networks. Different types of cost estimates are described. Neural networks are introduced as a tool for direct cost estimating at a predesign stage. Neural network components and characteristics, as well as different paradigms considered in this work are described.

The proposed system is described in Chapter 3 along with the limitations of detailed cost estimating methods at the early stages of project development when Request for Proposals (RFP) are required. A detailed description of the proposed conceptual cost estimating models is provided, including knowledge acquisition, design and training. Testing and evaluation are conducted to study the performance of developed models against actual costs. The results obtained are then presented and analyzed. Retraining of the neural network models is discussed.

Chapter 4 presents the developed decision support system. The chapter starts with the overall description of the system, the system's requirements, its components and their respective functions. The performance of the system is discussed and its limitations highlighted.

In chapter 5, summary and concluding remarks are made along with recommendations for future work.

CHAPTER 2- LITERATURE REVIEW

2.1 Current Cost Estimating Practice

An interview with potential owners initiates the cost estimating process at the company providing the data for this study. Subsequently, a request for proposal (RFP) is filled out and sent to the Head Office. A preliminary design is then performed for identification of structural members and for quantity take-off purposes. Material and labor costs are calculated individually for columns, joists deck and wall panels. The cost of "Planning and Engineering" is also calculated. Quotations for transportation and erection costs are requested from subcontractors. Markup is allocated individually to each of these cost items. After subtotals are added up for a general subtotal, an allowance for an overall markup is made before the addition of federal and provincial taxes, as applicable.

A contract with all project specifications is then drawn based on the prepared estimate. If considered acceptable, the contract is signed. Minor modifications, if any, can be negotiated and included in the contract itself. Otherwise, if the scope of the project is to be modified, the whole contracting process is repeated. Clearly, based on this process, in cases of aborted projects, a considerable estimating effort would be wasted. Figure 2, 3 and 4 describe current cost estimating practice for wall panels, steel framing and total direct cost, respectively.

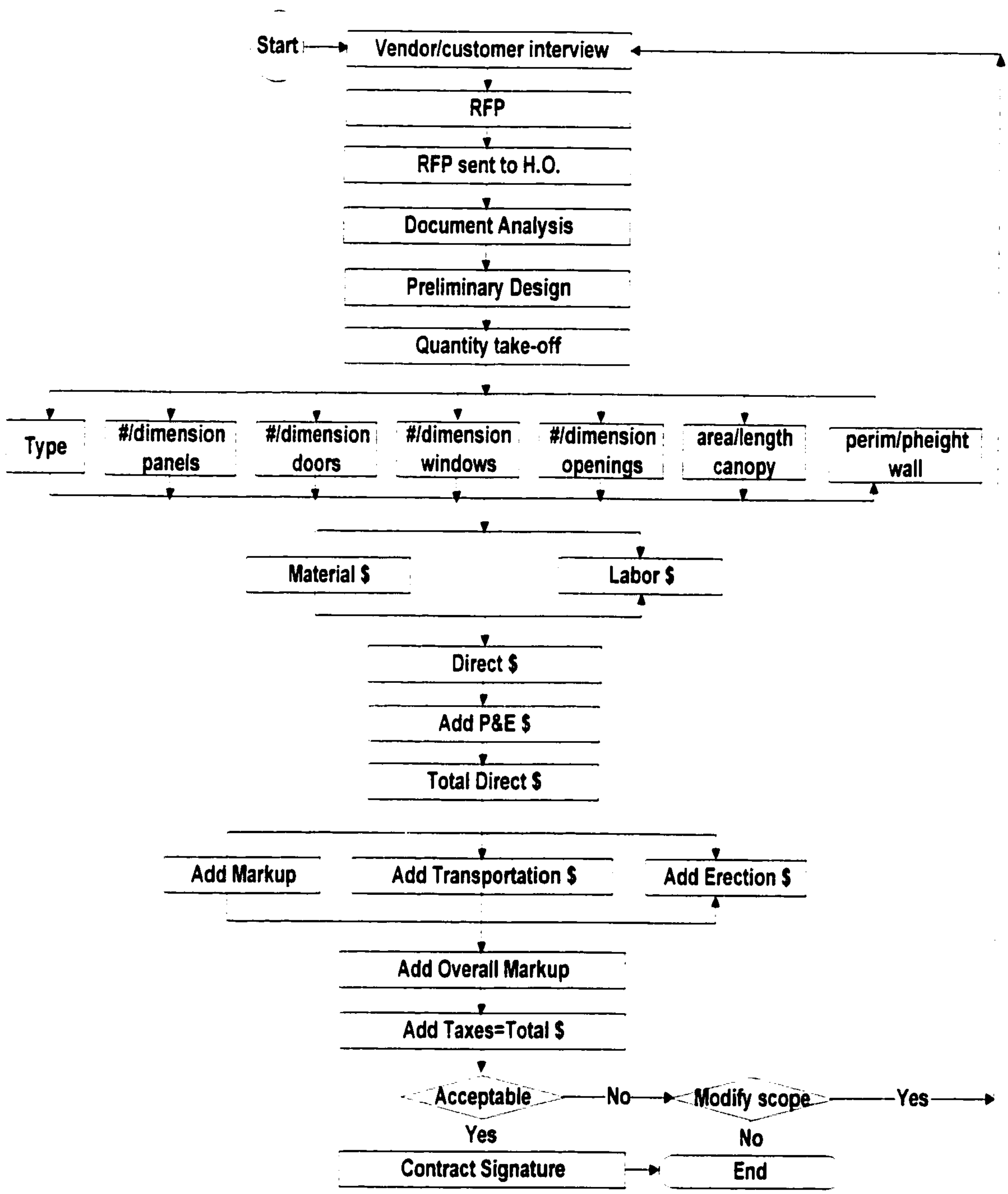

Figure 2 Current Cost Estimating Practice: Wall Panels

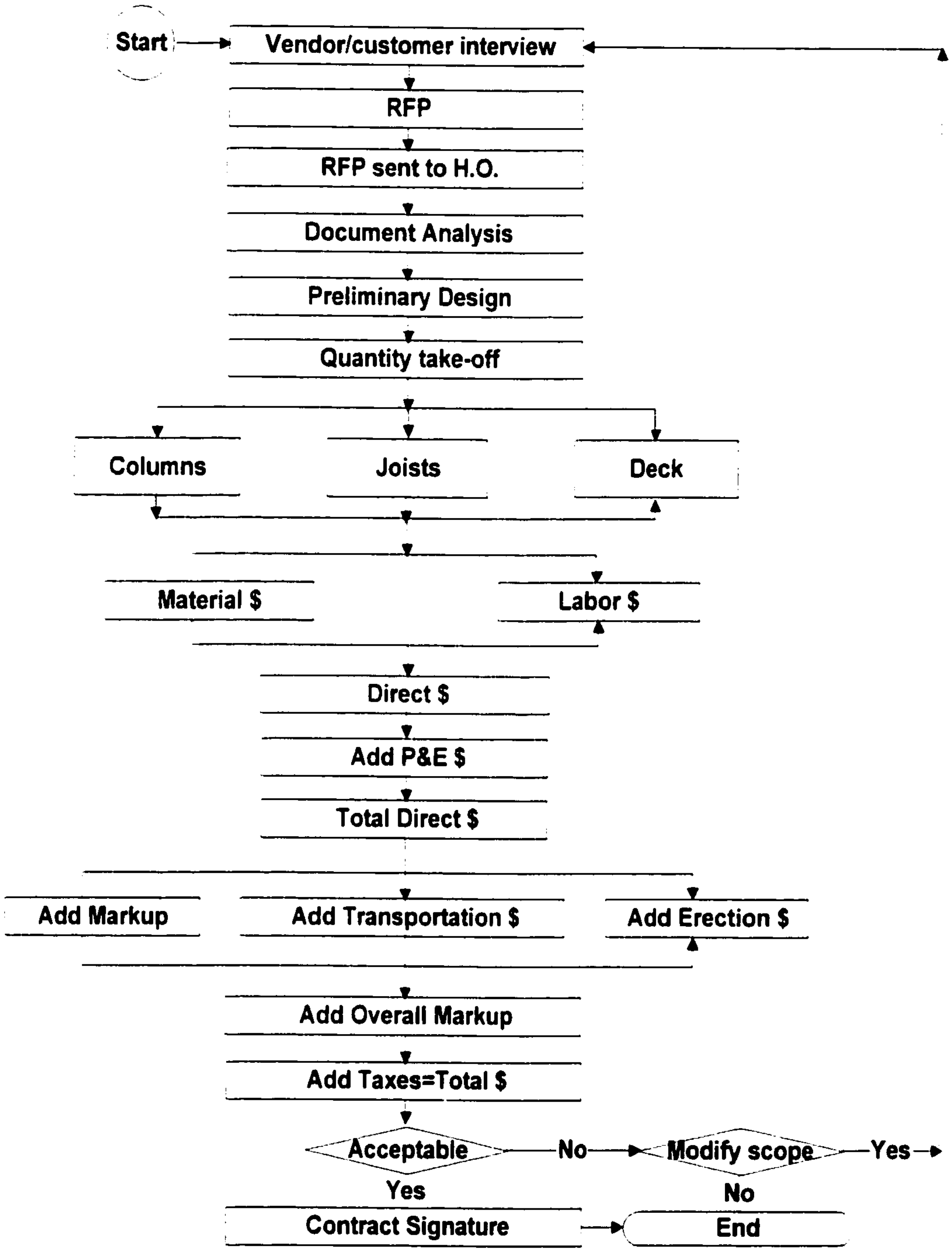

Figure 3 Current Cost Estimating Practice: Steel Framing

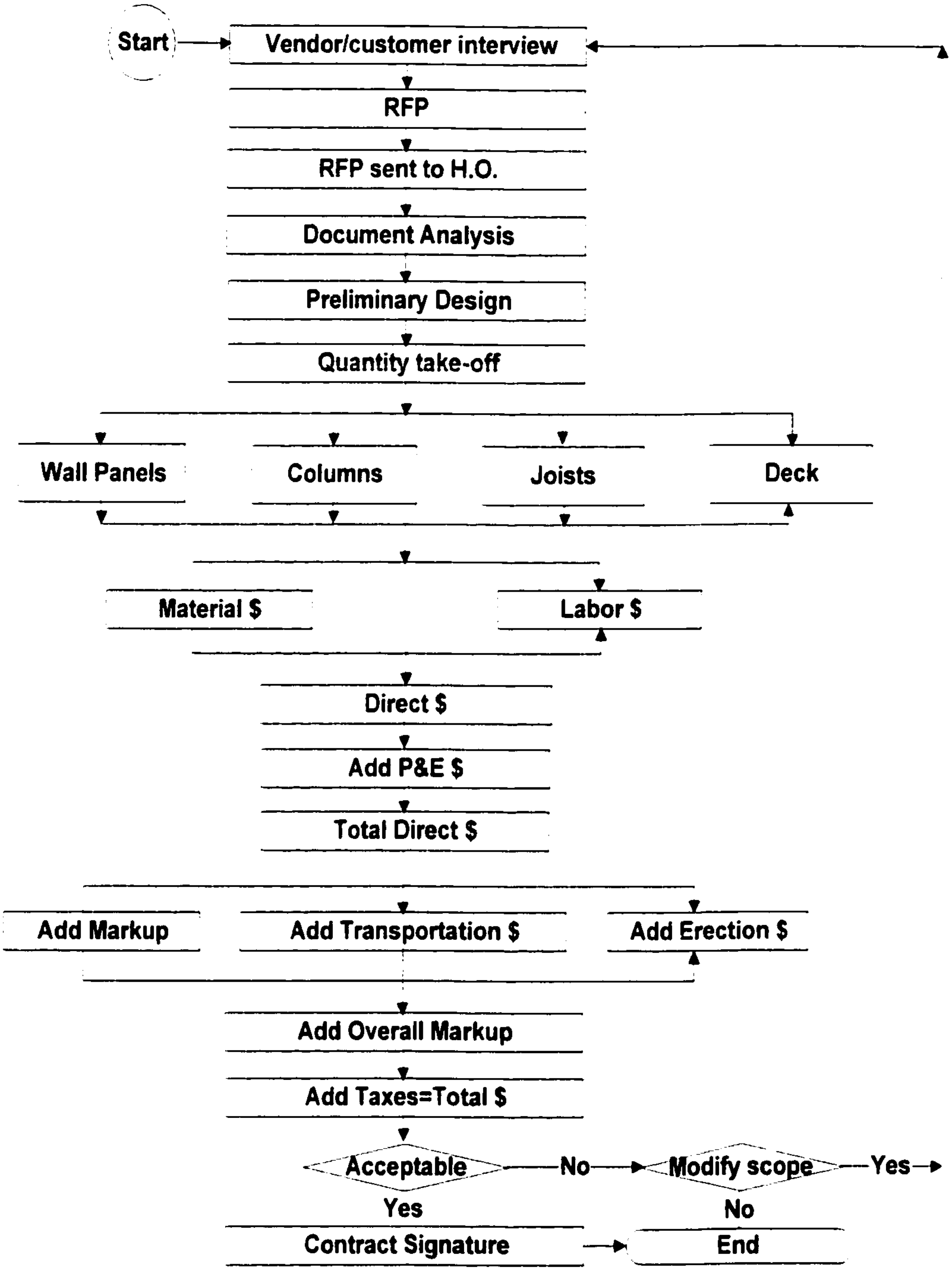

Figure 4 Current Cost Estimating Practice: Total Project

2.2 Cost Estimating

The accuracy of any estimate depends on the amount of information available at the time of the estimate. As stated in the Construction Industry Institute's 'Improving Early Estimates', (CII 1998) "...any cost estimate is assigned a range of accuracy (±percentage). These ranges narrow as the quantity and quality of information increase through the life of a project. This infers that estimate accuracy is a function of available information (scope definition), a generally accepted fact in engineering and construction". Good estimating practice and experienced personnel are also found to have considerable impact on estimate accuracy, specially on conceptual estimates, since at this stage the level of scope definition is low and often poorly defined (CII, 1998).

The CII's study highlights the following as major factors impacting estimates' accuracy:

1) Quality and amount of information available for preparing the estimate
2) Time allocated to prepare the estimate
3) Proficiency of the estimator and the estimating team
4) Tools and techniques used in preparing the estimate

Accordingly, estimates are classified and their corresponding range of accuracy defined. The cost estimate classifications by the Association for Advancement of Cost Engineering (AACE) International and the Construction Industry Institute (CII), adapted, are shown in Table 1 and Table 2, respectively.

Table 1 AACE International Cost Estimation Classifications (18R-97)

Estimate Class	Level of Project Definition (%)	End Usage (Typical Purpose)	Expected Accuracy Range (%)
Class 5	0 to 2	Concept Screening	-50 to +100
Class 4	1 to 5	Study or Feasibility	-30 to +50
Class 3	10 to 40	Budget or Control	- 20 to +30
Class 2	30 to 70	Control or Bid/Tender	-15 to +20
Class 1	50 to 100	Check Estimate or Bid	-10 to +15

Table 2 Construction Industry Institute Cost Estimate Definitions (CII SD-6)

Estimate Class	Percentage Range	Description/ Methodology
Order of Magnitude	± 30 to 50	Feasibility Study: cost/capacity curves
Factored Estimate	± 25 to 30	Major equipment: cost/factors
Control Estimate	± 10 to 15	Quantities: mech./elec./civil drawgs.
Detailed or Definitive	±<10	Based on detailed drawings

This study will focus on estimates prepared at a predesign stage, when the level of project definition is within 10 to 40%. The expected accuracy range for these estimates is between ±20 to 30%. This is in line with AACE International (Class 5, 4, and 3 estimates) and CII (Order of Magnitude and Factored) classifications. The terms conceptual, parametric and order of magnitude are used interchangeably in this thesis to refer to the type of estimates described above.

A conceptual cost estimate uses main parameters (parameters that have the most significant cost impact on the product being estimated) of a project to determine its cost. It focuses on cost drivers, the specified design and/or planning characteristics that have a predominant effect on the cost of a project. Once the cost drivers are identified, cost models for the generation of conceptual estimates can then be developed. Reliance on conceptual cost estimates generated by properly developed and carefully evaluated cost models can save the user time and resources not only in the evaluation of project alternatives but also in the checking of detailed cost estimates prior to bid submittals (CII 1998, U.S. Department of Defense 1995, Barrie and Paulson 1992).

Conceptual cost estimates date back to World War II (U.S. Department of Defense 1995), when a demand for military aircraft in numbers and models far exceeded anything the aircraft industry had ever manufactured before. Industrial engineers were then led to use a type of statistical estimating, suggested by T. P. Wright in the Journal of Aeronautical Science in 1936, to predict the unit cost of airplanes. These equations could be used to predict the cost of airplanes over long production runs, a theory which came to be called the learning curve (U. S. Department of Defense 1995).

However, while the learning curve technique proved most useful for predicting the behavior of recurring cost, there were still no techniques other than detailed estimating for predicting what the first unit cost might be (a key input to the learning curve equation). In the mid 1950's the Rand Corporation, in Santa Monica, California, developed the most basic tools of the cost estimating discipline, the Cost Estimating Relationship (CER), and merged the CER with the learning curve to form the foundation of parametric aerospace estimating (U. S. Department of Defense 1995).

The use of CERs constituted a breakthrough in cost estimating, for cost analysts saw, for the first time, the promise of being able to estimate, to a reasonable degree of accuracy and in a timely manner, the cost of proposed new systems. Since then, the state of art in parametric estimating has been steadily improving by a considerable growth in the number of practitioners, important methodological improvements, and greatly expanded databases (U.S. Department of Defense 1995).

Parametric estimates are used to assist: 1) owners in making go-no-go decisions, 2) owners and estimators in the definition of project scope and characteristics, 3) owners and designers in estimating C.O.'s, 4) estimators in the checking of detailed estimates, 5) production managers in cost control of the work in progress, and/or 6) contractors in last minute bid preparation (CII 1998, U.S. Department of Defense 1995, Melin 1994, Paek 1994, Barrie and Paulson 1992, Carr 1989, Karshenas 1984).

Over the past several years industry and professional estimating associations (e.g., International Society of Parametric Analyst (ISPA), Society of Cost Estimating and Analysis (SCEA)) have been actively working to explore the expanded opportunities for the use of conceptual cost estimating techniques for business proposals. ISPA was formed in 1978 when a parametric estimating user's group evolved into a more generic Society (U.S. Department of Defense 1995).

As part of the efforts devoted to the improvement of conceptual estimates, CII Research Team 131, identified in the report entitled "Improving Early Estimates" the following primary factors in preparing estimates:

1) Alignment of objectives between customer and cost estimating team.
2) Standardization of the cost estimate preparation process.
3) Selection of estimate methodology commensurate with the desired level of accuracy.
4) Documentation and communication of estimate basis and accuracy.
5) Review and checking of estimate.
6) Feedback from project implementation.

Alignment ensures mutual understanding between user and client regarding the level of scope definition, and as such the estimate expected range of accuracy. Effective communication is essential during the estimating process and standardization of the process becomes a must for consistency and reliability of the estimates prepared. A standardized process defines the basis of the estimate and facilitates its review and future. It, further, supports effective communication with owners. To improve conceptual estimates, the estimating process must be a continuous cycle. Actual cost information from completed projects must be captured in a feedback system that can be integrated into the cost database for use in preparing future estimates (CII 1998).

2.3 Neural Networks

Neural networks (NNs) are not new, they were introduced half a century ago, creating together with knowledge based expert systems (KBESs) the field of Artificial Intelligence, AI, (Moselhi 1998a). NNs and KBESs did not receive equal attention. The interest in these two AI techniques varied over the years, with a notable sharp decline in NNs' research in the early 1970s. NNs, however, have received considerable attention in recent years, with the rapidly increasing computational power and concurrently declining cost of computers (Moselhi 1998a). NNs try to reproduce the generalization abilities of a human neural system (Moselhi 1998, Flood and Kartam 1994, Moselhi 1993, Garret 1992, Garret et al. 1992, Moselhi 1991b, Rumelhart 1986).

It is estimated that the human brain contains approximately 100 billion neurones linked by 10^{15} interconnections, and when functioning actively the brain would be firing at a maximum rate of 1,000 pluses/second, approximately. NNs, on the other hand, consist essentially of a number of simple processing elements or artificial neurones linked with a set of interconnections representing, respectively, neural cells or neurones and their axons or semi connectors in the human brain. The processing elements are arranged and organised in different forms, depending on the type of network and its paradigm (Moselhi 1998a, Moselhi et al 1993, Moselhi et al. 1991b). Figure 5 depicts the most commonly used type of NNs, known as the feed-forward or back-propagation (Rumelhart 1986). This type and similar architecture such as general regression neural networks (GRNN) are most suited for pattern recognition and forecasting class of problems.

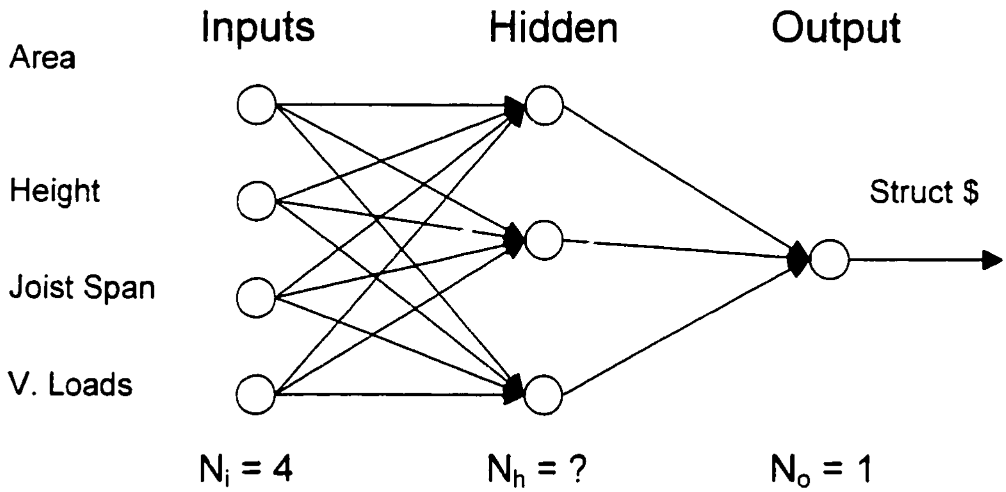

Figure 5 Feed-forward Network (Moselhi 1998a)

Feed-forward networks gain their knowledge, and hence their problem-solving capabilities by learning from cases encountered, in a manner similar to a human gaining work experience. Those cases are called training examples, where for each case the input parameters form an input pattern and the desired output parameters form an associated output pattern. As such, each training example represents an added experience to the network. In training, the network generalizes the knowledge implicit in the training examples, by associating the input to the desired output, and becomes capable of providing solutions to new problems, even with noisy and incomplete input data. It follows that a prerequisite for developing any practical application is to identify the input and output parameters and to map them into a suitable pattern (i.e. defining the number of processing elements in the input buffer and output layer, see Figure 5). Clearly this requires a complete and comprehensive understanding of the domain of application. The optimum number of nodes in the hidden layer, however, is determined after a series of trials and a default number to start with is required. NeuroShell 2 (NeuroShell 2 1996), a commercial neural network software, suggests, in its manual, an equation for the calculation of the number of the nodes in the hidden layer.

$$N_h = \frac{(N_i + N_o)}{2} + \sqrt{N_{trn}} \qquad (1)$$

Where: N_h = Number of nodes in the hidden layer

N_i = Number of nodes in the input layer

N_o = Number of nodes in the output layer

N_{trn} = Number of training examples

The input data is presented to the input layer, normalized, and multiplied by its connection weight. Calculated the weighed inputs, they are summed at each node to produce an activation value, which is then modified by a selected transfer function. The transfer function can take many forms: logistic, linear, tangent, etc. (NeuroShell 2 1996). The output of the neurons in the hidden layers(s) will then be multiplied by the respective weights, this product summed up, and a new activation value generated. This new value will then be modified by a transfer function, and an output for that processing element is calculated (NeuroShell 2 1996, Garret et al. 1992, Moselhi et al 1991b, Rumelhart 1986).

The error (difference) between desired output (D) and that generated by the network (N) is termed δ. The average squared error over all the training examples is (Moselhi 1998a):

$$E = \frac{1}{2t}\sum_{j=1}^{N_{trn}} \sum_{i=1}^{N_0}\left(D_{ij} - N_{ij}\right)^2 \qquad (2)$$

in which E = Average of squared errors,

N_{trn} = Number of training examples

N_0 = Number of nodes in the output layer

The weights (W's) are adjusted by an incremental variation proportional to the error (δ), formulated in a manner that reduces the error E in Eq. 2, as shown in Eq. 3:

$$W_{new} = W_{old} + \Delta W \qquad (3)$$

in which $\Delta W = \eta\delta X$

η = Learning rate coefficient

($0<\delta<1$), and

X = Input value

Other forms for Equation 3 have been proposed in the literature. The fundamentals of NNs can be found in a number of textbooks (Moselhi 1998a).

Different architectures and training rules define different types of neural networks (Moselhi 1998a, Kartam et al. 1993, Moselhi et al. 1991b) however, backpropagation (Rumelhart et al. 1986) is the training algorithm most commonly used for the development of civil engineering, and more specifically construction management, applications (Moselhi 1998a, Flood and Kartam 1994, Kartam et al. 1993, Garret Jr. 1992, Garret et al. 1992, Moselhi et al. 1991b). Backpropagation has been briefly described in this thesis for continuity.

General regression neural network (GRNN), like backpropagation, is essentially a feedforward network that consists of 4 (four) layers as shown in Figure 6. Unlike backpropagation type networks, GRNN has 2 (two) hidden layers, the first is called the pattern units, and has the same number of nodes as the number of project cases or training examples. The second hidden layer consists essentially of 2 (two) nodes. Further, this type of network does not propagate the error as in backpropagation, it is rather known to be a one-pass network (Specht 1991). GRNN is described by Equation 4:

$$\hat{Y}(X) = \frac{\sum_{i=1}^{n} Y^{i} \exp\left(-\frac{D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^{n} \exp\left(-\frac{D_i^2}{2\sigma^2}\right)} \qquad (4)$$

in which

$$D_i^2 = (X - X^i)^T (X - X^i) \qquad (5)$$

$\hat{Y}$ = Conditional mean of the probability function

X = Random variable

Y^i = Sample value

D_i^2 = Scalar function

σ = Width of the probability function

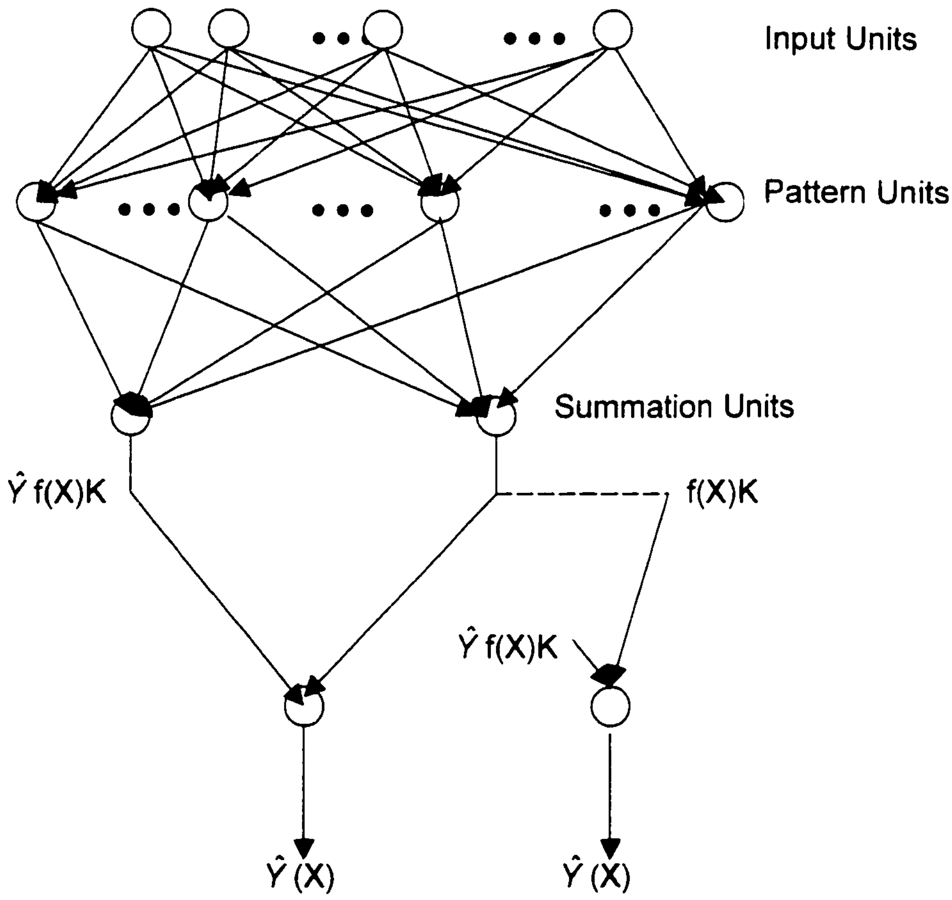

Figure 6 GRNN (Specht 1991)

Although application of neural network in civil engineering only go back to the late 1980's (Flood and Kartam 1994), by 1994 neural networks already covered a range of topics as diverse as process optimization, seismic hazard prediction, classification of nondestructive evaluation signals, selection of formwork systems and cost estimating (Flood and Kartam 1994).

Backpropagation neural networks have been used in the development of applications such as: modeling reinforced concrete (Mukherjee and Deshpande 1995), concrete strength (Williams et al. 1992), modeling soil correlation (Goh 1995), simulating structural analysis (Rogers 1994), predicting estuarine instabilities (Grubert 1995), predicting pile capacity (The et al. 1997), damage of prestressed concrete piles (Yeh et al. 1993), average and peak traffic volumes (Lingras and Adamo 1996), estimating construction productivity (Sonmez and Rowings 1998, AbouRizk and Portas 1997, Chao and Skibniewski 1994, Karshenas and Feng 1992), identification of structural damage (Barai and Pandey 1995, Elkordy et al. 1993), environmental engineering (Basheer and Najjar 1996), cost forecasting (Boussabaine and Kaka 1998), vertical formwork selection (Kamarthi et al 1992), selection of flooring systems (Issa and Fletcher 1993), and estimating resource requirements (Elazouni et al. 1997).

In the area of cost estimating, applications have been developed for parametric cost estimating of: low-rise structural steel buildings (Siqueira 1999, Moselhi and Siqueira 1998, Siqueira and Moselhi 1998a, Siqueira and Moselhi 1998b), change orders (Moselhi 1998b), highway projects (Hegazy and Ayed 1998), manufacturing industry (Bode, 1998), timber bridges (Creese and Li 1995), carbon steel pipes (de la Garza and Rouhana 1995), and pumps (McKim 1993).

Neural networks exhibit a number of advantages that makes it especially suitable for cost estimating. These include (Flood and Kartam 1994, Kartam et al. 1993, Garret et al. 1992, Moselhi et al. 1991b):

1) ability to account for complex cases requiring large number of parameters to be considered in parallel;
2) learning by example, associating inputs to output(s);
3) speed of computation;
4) generalization capabilities; and
5) fault tolerance.

Neural networks, however, exhibit also shortcomings (Flood and Kartam 1994; Kartam et al. 1993; Moselhi et al. 1991b):

1) they are not transparent enough to provide explanation facility or reasoning behind the generated solution;
2) they are sensitive to the organization and preparation of the data used in training, as well as, to a larger degree, on the configuration of the network itself;
3) they require the availability of a sizable number of training examples that may be difficult to assemble.

CHAPTER 3 - PROPOSED NEURAL NETWORK MODELS

3.1 General

The proposed automated cost estimating system represents a cost-effective response to the cost estimating process of low-rise structural-steel buildings, building on industry knowledge. Detailed cost estimates are traditionally performed for this class of buildings, since a number of variables are to be considered in parallel. This process, however, does not support timely response to industry needs. In many cases, RFPs are refused simply because of lack of estimating resources.

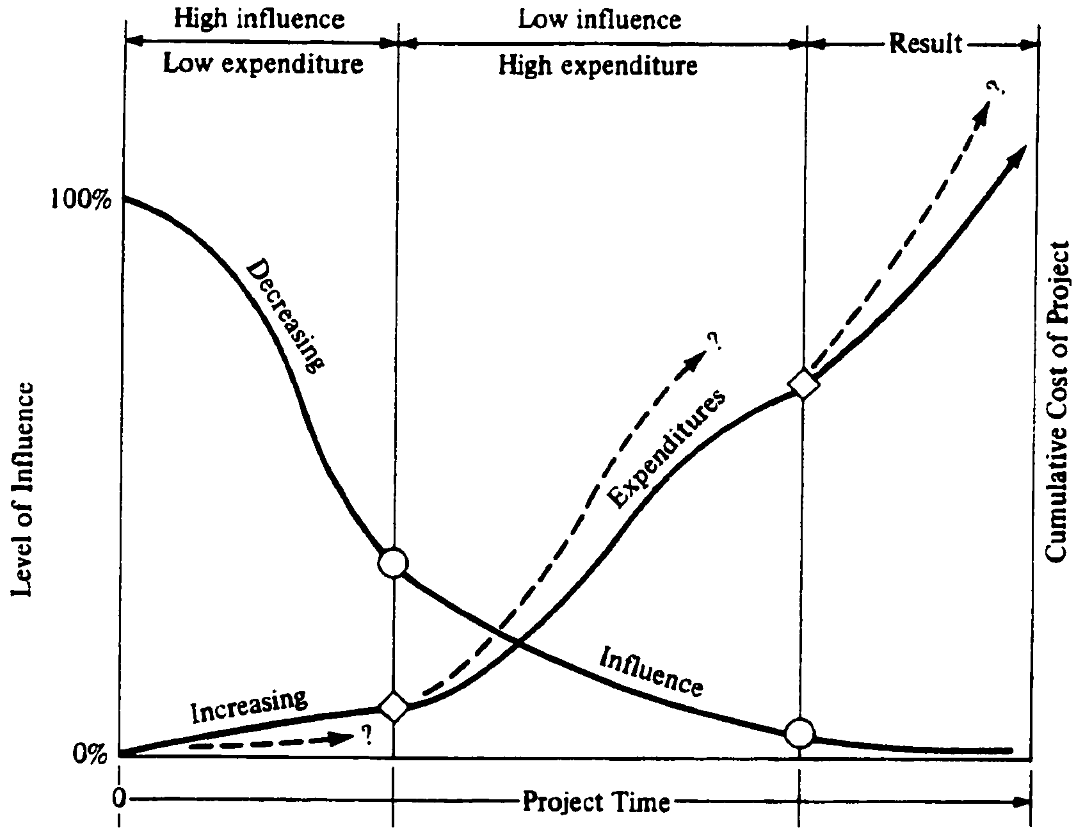

Figure 7 Level of Influence on Project Costs (Barrie and Paulson 1992)

More, as shown in Figure 7, the cost of a building is essentially determined in the early stages of a project. Therefore, the generation of conceptual cost estimates for different scenarios at a predesign stage is crucial for effective cost management of the delivered projects (Barrie and Paulson 1992).

This system proposes the generation of conceptual cost estimates at the planning stage of a project, when detailed design has not been performed yet, to respond to market needs in a timely fashion. This type of estimates provides for reasonable accuracy in the estimating of direct cost of buildings (i.e. material, labor and subcontractors' costs), assisting in the decision making process, in the definition of project scope and characteristics and in the checking of detailed estimates prior to bid submittals. Compared to detailed estimates prepared at the planning stage, the reduction of estimating time and cost attributed to the use of conceptual estimates outweighs the estimating accuracy at this stage.

For the definition of project scope and characteristics, a number of conceptual cost estimates for different project alternatives can be generated in a timely fashion. When, and if, meeting the client's budget and needs, the chosen project alternative is sent to the Head Office for detailed estimating. In cases where no alternative is chosen, the project is aborted before any design effort is committed (Figure 8). This process differs from current practice in allowing for the generation of a number of reliable conceptual cost estimates to help in determining which projects are to go for detailed estimating.

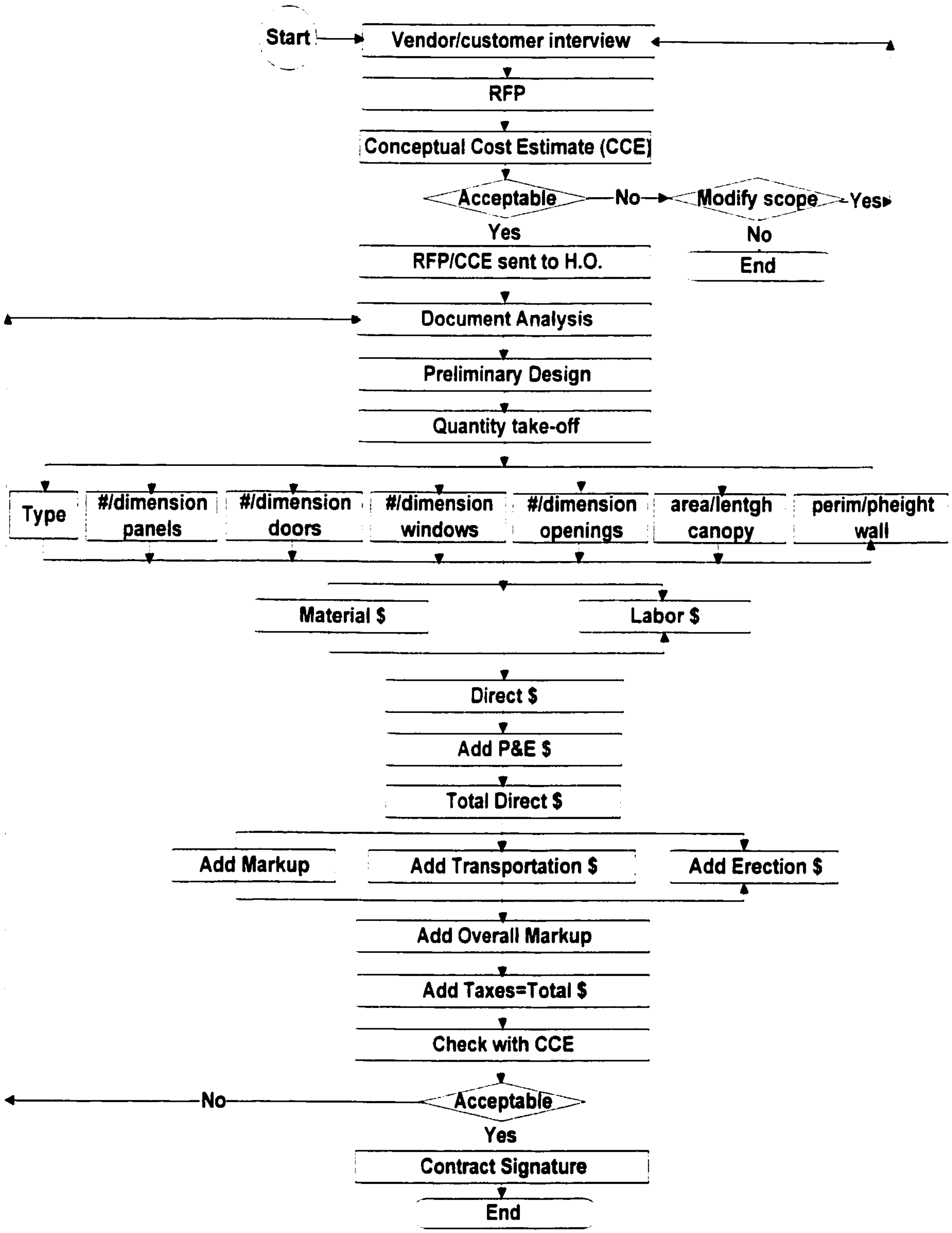

Figure 8 Proposed Cost Estimating System

At the moment, the project acceptance rate at the company providing the data for this study is approximately 15%, while a number of RFPs are turned down for lack of estimating capacity. The utilization of the present model is expected to free up estimators' time, which will be dedicated to the estimating of pre-selected projects, found initially acceptable to owners. Thus, capitalizing on considerably more business opportunities.

The proposed automated cost estimating system (ACE) includes three parametric cost estimating models based on neural networks. Neural networks are known for their learning and generalization capabilities (Moselhi et al. 1991b), which make them ideal for the development of decision-support tools for analogy-based problems and forecasting models, such as the problem at hand. Neural networks, as tools, are capable of identifying a relationship between the direct cost of a building and the various parameters defining this building.

ACE utilizes three neural network models developed for the generation of:

1) an order of magnitude cost estimate,
2) a parametric cost estimate of the wall, and
3) a parametric cost estimate of the structural steel framing.

The data used in the development of the system was mainly collected over a three-month period (March to May 1997). Another ten completed projects were collected later in the Fall of that year. The data was all collected at the same manufacturing plant, in order to ensure consistency in 1) estimating and design practices, 2) productivity levels, and 3) material, labor and equipment rates. Canam Manac, a large manufacturer of low-rise structural steel buildings in Canada provided the researcher open access to: 1) visits to its main fabrication plant, 2) interviews with estimating, design and management teams, and 3) documents pertaining to collected building projects, fabricated and constructed between 1994 and 1997.

The documents collected for each project, in a joint effort of research, management, design and estimating teams, consist of: 1) detailed estimate, 2) contract (with project specifications) and change orders, 3) blueprints, and 4) final cost report.

The final cost report includes the actual costs of a project without and with markup. Markups, allocated to individual cost items, may vary considerably to account for market conditions, the contractor's need of work, number of bidders, etc (Hegazy and Moselhi 1994). It was then decided that only the direct cost of fabricated buildings (i.e. material, labor and subcontractors' costs) would be used in the developed system.

The allocation of markups, as it is presently the case, will continue to be determined by the management team. This feature does not only help in reducing the variability and eliminating the subjectivity in the data used for estimating, but also provides flexibility in accounting for market conditions and the risk associated with each individual project.

The developed system is limited to conceptual cost estimating of prefabricated low-rise structural-steel commercial and industrial buildings. Low-rise buildings are defined by the National Building Code of Canada as buildings with height to width ratio less than 1, and mean roof height less than 20m (NBCC, 1995). A numerical example is worked out in order to illustrate the use of the system and demonstrate its level of accuracy.

Figure 9 is a graphical representation of the development of an automated cost estimating system. The figure indicates the development from data collection and analysis through design and training of the neural networks, testing and evaluation of the models, and design of windows for data entry and output display. The cost report allows for the conversion of system's output into a bid proposal.

3.2 Proposed Cost Estimating Models

Current industry practice indicates the generation of 3 types of cost estimates: 1) total cost; 2) cost of wall panels; and 3) cost of steel frame. Accordingly, three neural network models were developed: order of magnitude (OM), for the generation of an order of magnitude type estimate, a parametric cost estimate for the building walls (PW) and a parametric cost estimate for the structural steel framing (PS) of the building.

These models aim at estimating planning, engineering and fabricating costs, by using a project's main parameters. This makes the models a good tool to use at the predesign stage, when there is insufficient definition of scope and characteristics to quantify required labor and material for a detailed cost estimate.

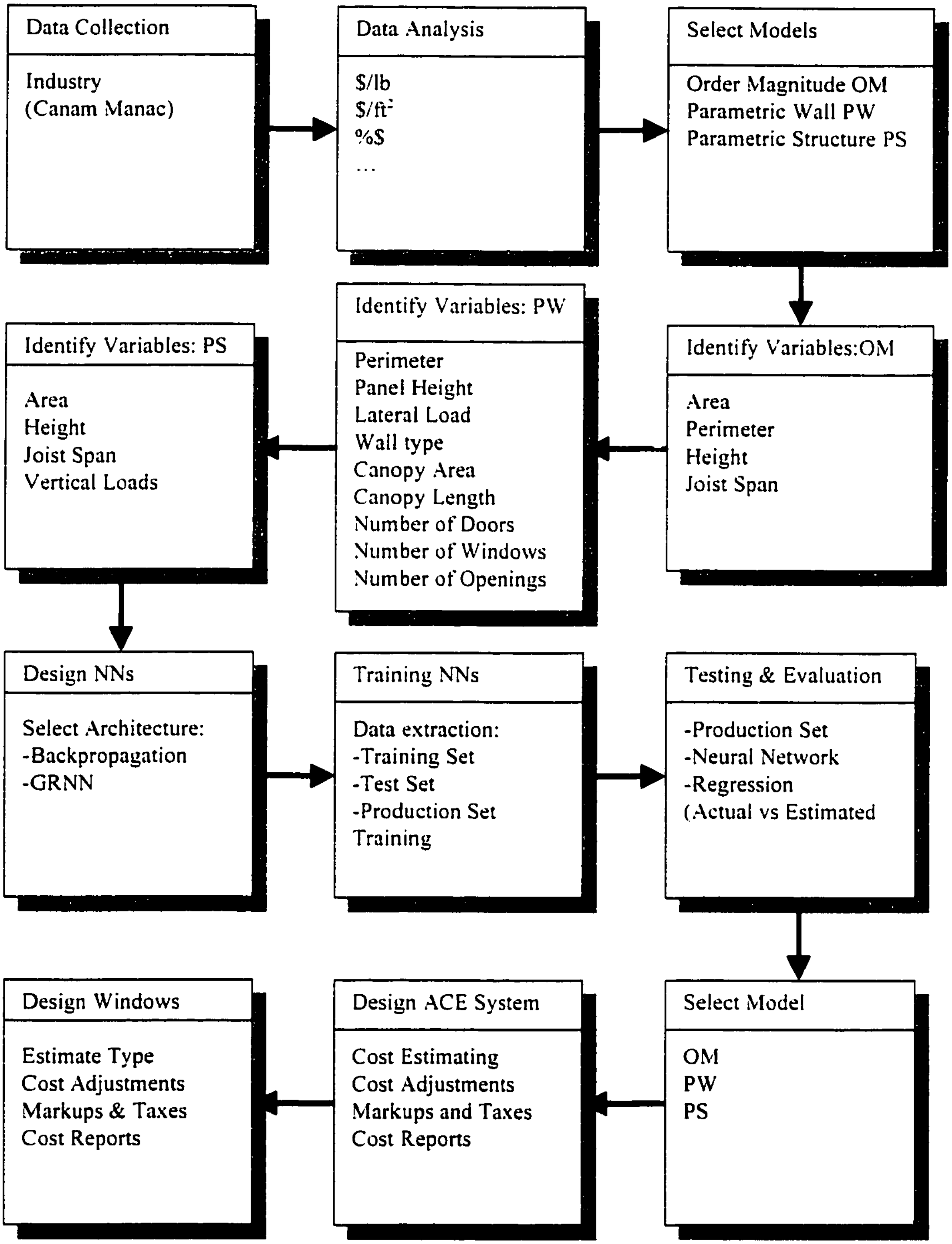

Figure 9 Development of an Automated Cost Estimating System

3.3 Data Collection and Analysis

Seventy-five low-rise structure-steel building projects, fabricated and built between 1994 and 1997, were mostly collected over a three-month period. Four types of project documents containing cost and non-cost data describing the individual characteristics of each building were verified for data extraction: 1) contract (with project specifications) and change orders, 2) blueprints, 3) detailed estimate, and 4) final cost report. Figure 10 exhibits a sample the collected documents

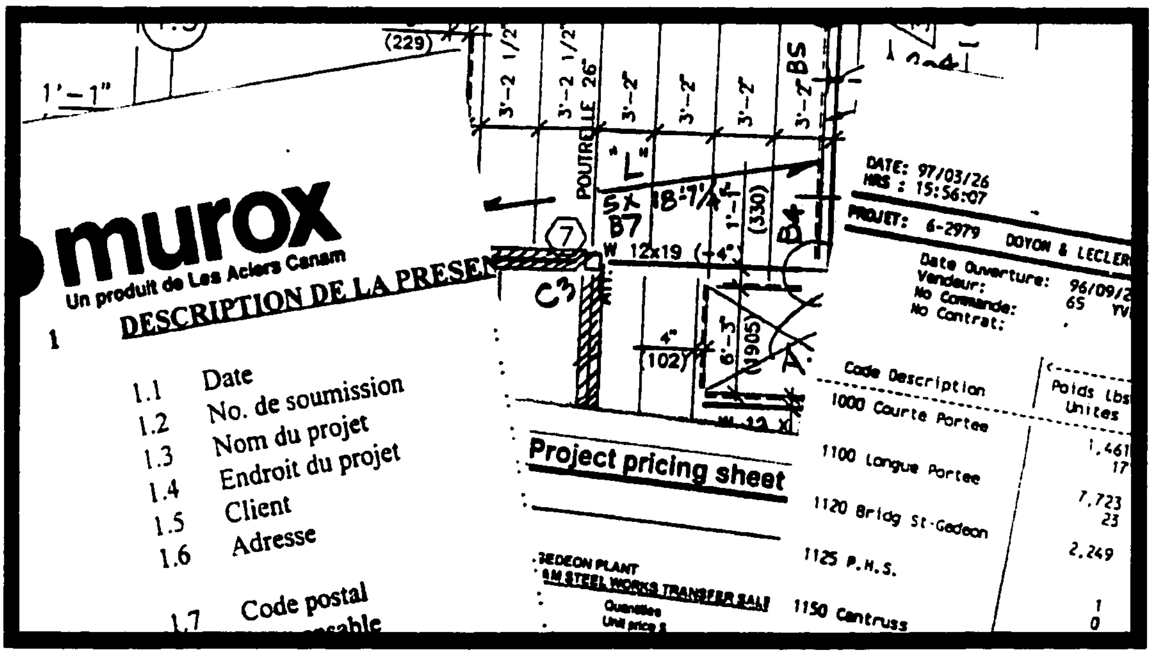

Figure 10 Collected Project Documents

These documents were presented in different formats, reflecting the company's estimating and accounting standards overtime. Special care was dedicated to the data extraction to ensure that the variation in type of reporting, over the years, would not impact the costs actually incurred. Differences in definitions and inconsistencies found in the projects' documents were carefully identified and clarified with design and estimating teams. A consistent method for capturing and recording information from completed projects was implemented.

Cost elements were grouped, as per the detailed cost estimate and final cost report, and associated to the main cost parameters (columns, joists, deck and wall panels). Cost parameters include all planning and engineering, labor, material and subcontractors' costs. Overhead and profit were not included. As well, costs related to site improvements and/or foundation work were excluded. A list of estimate parameters was then compiled based on the collected documents and feedback from design and estimating teams.

A data entry sheet (see Appendix I) was designed for standardization of data collection, organization, indexing, recording, and analysis. The emphasis throughout was to describe completed projects, recording and describing parameters in ways that avoid misinterpretation. For consistency, adjustments were made for projects with different scope. To account for the effects of inflation on the historical data, and have comparable data, the data were indexed to January 1997, using R.S Means (RS Means 1997). Care was taken in ensuring consistency of data: 1) costs of labor/hour and material/pound were checked to verify if they had increased at the same rate; 2) units used were converted when necessary to assure compatibility; and 3) historical costs checked to reflect the actual costs incurred.

Data were analyzed for consistency and parameter (CISC 1998) values checked for reasonableness in order to ensure same definition, in terms of content. Individual calculations of: 1) cost per pound of columns, joists and deck; 2) cost per square foot of building area for columns, joists and deck; and 3) % of cost of columns, joists, and deck with respect to total structural cost were performed. Data outliers were identified, studied, and verified with the estimating and design teams of the company. Non-representative projects (2 projects) and projects with non-explainable anomalies (1 project) were excluded, and errors encountered during data preparation were corrected.

In an effort to increase the accuracy of the proposed cost estimating model, the collected data was broken down into four project categories: 1) standard, or typical buildings, 2) buildings with mezzanine, 3) buildings with overhead cranes and 4) buildings with mezzanine and overhead cranes. The standard case, being the most common, was used in the development of the neural network models. Accordingly, the data of 36 standard projects were used in the development of the proposed neural network models.

The area of the buildings included in the data sample ranged from 2,040ft^2 to 73,185ft^2 while height and span of the joists ranged from 12.5ft to 33ft and 20.6ft to 75ft respectively. The perimeter of the buildings ranged from 129ft to 1307ft. Dead and live loads were added up for simplification. The vertical load parameter presented values ranging from $41.9 lbs/ft^2$ to $85.2 lbs/ft^2$. The values of the lateral load ranged from $6.05 lbs/ft^2$ to $23 lbs/ft^2$.

A data analysis revealed the main input parameters to be used in the design and training of each network model to be developed. These are the predominant cost drivers of these projects. These parameters define the building size, envelope, characteristics and amount of material and labor required to the fabrication of a building. Some parameters were combined for simplification, such as dead and live loads combined into vertical loads, and width and height of canopies combined into canopy area. The span of joists was calculated.

Area, perimeter, building height and vertical loads were the parameters deemed essential to the development of an order of magnitude type estimate. For a parametric estimating model for the cost of the building walls the parameters selected are: perimeter, panel height, lateral load, type of wall finishing, canopy area, canopy length, number of doors, number of windows, and percentage of openings as a function of the area of the wall. Perimeter and height clearly define quantities involved. Area, height, joist span and vertical loads (dead and live loads) were identified as the main structural parameters, directly correlated to the fabrication cost of the structural steel framing of the building. While area considerably impacts structural cost, the span is an important factor influencing directly the weight of structural steel joists, which impacts columns' costs. Further, the height clearly impacts the cost of columns.

It is interesting to notice that most order of magnitude cost estimates, such as cost estimates based on R.S. Means cost books, are based on $\$/ft^2$, and do not consider different project parameters. These estimates require essentially project area, while in some cases allowing for cost adjustments to account for perimeter and height. These estimates provide a lump sum estimate including erection costs, which can vary considerably, depending on market conditions. In this thesis, after the training of networks considering both selected parameters and a larger set of parameters, it became clear, through comparison of parameter weights, that the main parameters selected by data analysis were the parameters considerably impacting project cost. Table 3 depicts the neural network models to be developed with their respective input and output parameters,

Table 3 Developed Neural Network Models

	NEURAL NETWORK MODELS		
	OM TOTAL	**WALL**	**STRUCTURE**
INPUTS			
Area	●		●
Height	●		●
Joist Span	●		●
Vertical Loads			●
Perimeter	●	●	
Panel Height		●	
Lateral Load		●	
Wall Type		●	
Canopy Area		●	
Canopy Length		●	
# Door		●	
# Windows		●	
% Openings		●	
OUTPUT			
$ OM TOTAL	●		
$ WALL		●	
$ STRUCTURE			●

3.4 Design and Training of the Networks

The parameters used in the development of the neural network models are all quantitative. Data were normalized for confidentiality and for effective training of the models being developed. The normalization of training data is recognized to improve the performance of trained networks (Flood and Kartam 1994, and Hegazy et al. 1994).

The data sample (thirty-six projects) was divided into three subsets: training, test, and production. These sets contained, respectively, 60%, 20%, and 20% of the project cases considered in the data sample. The data extraction was performed randomly by NeuroShell 2. The training set was used for training of each network. The test set was used to check the performance of the learning process, during the network's training. The production set contained the project cases used to evaluate the performance of each network once training was over. The network had not seen those cases during its training. Performance was primarily measured against the accuracy observed in the production set. Once the networks were performing with an acceptable percentage of error, they were considered trained and ready to assist the user in generating cost estimates.

For a new project to be estimated the user first extracts the values associated with the parameters previously described. The input parameters are keyed into the model and the network recalled. The network will automatically predict the direct cost of the project. The predicted cost may then be adjusted for buildings other than the standard type used for network training. The cost estimate is finally reviewed and adjusted, by the allocation of different markups to individual cost items, as well as the allocation of a general markup and the application of taxes.

3.4.1 Wall Estimate

The developed model provides the user with parametric cost estimates of prefabricated walls (Siqueira and Moselhi 1998b). In an effort to increase the model's accuracy, the collected data was broken down into standard (width = 10ft) and non-standard (width < 10ft) wall panels. The neural network model is trained for standard panels, and the generated estimates assume all panels to be standard. An algorithm has been developed to estimate the additional cost of non-standard wall panels. The algorithm will calculate adjustments to be made to the estimated direct cost, based on the width and number of non-standard panels, and/or special painting.

The data used in the training of the network is shown in Table 4. Nine parameters (inputs) are used in the design and training of this neural network model. These parameters are considered significant in estimating the direct cost of the prefabricated wall panels, and they include: perimeter (Perim), panel height (PHt), lateral load (Lload), type of wall (Wall), area of canopy (CA), canopy length (CL), number of doors (Door), number of windows (Win), and percentage of openings as a function of the surface area of the wall (Opn).

Table 4 Data Characteristics: Wall Panels

	Perim (ft)	**PHt** (ft)	**Lload** (lbs/ft^2)	**Wall** ($/ft^2)	**CA** (ft^2)	**CL** (ft)	**Door** (un)	**Win** (un)	**Opn** (%)	**Wall$** ($)
Min	129	12.5	6.1	4.25	0	0	0	0	0	19,140
Max	1,307	31.0	23.0	5.40	31	323	13	15	27	189,600
Mean	398	19.9	10.2	5.20	3.5	26	2.8	2	7	65,620
S. D.	272	4.4	3.5	.40	7.7	62	2.53	4.0	6	46,780

Table 5 Networks' Configurations: Wall Panels Cost NNs

	N-7	N-8	N-9	N-10	N-11	N-12	N-13	N-14	N-15
Input nodes	9	9	9	9	9	9	9	9	9
Hidden nodes	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Output nodes	1	1	1	1	1	1	1	1	1

A single layer backpropagation architecture was used in the design of the model. The number of nodes in the hidden layer, calculated by default, according to equation (1), is 11 (eleven). Nine network models were developed, with the number of the nodes in the hidden layer varying from 7 (seven) to 15 (fifteen) for the identification of the network with best performance. The input and output parameters were kept constant in all the nets. The configuration (i.e. structure) of the 9 (nine) networks is described in Table 5.

Performance was primarily measured against the accuracy observed in the production set. The training of all the networks was interrupted after 50,000 learning events had occurred with no improvements in the minimum average error of the network associated with the test data set. An event is the presentation of a single training example to the neural network (NeuroShell 2, 1996). The training examples were presented to the network in a sequential order.

The network with 13 nodes presented better performance. The network's training time was 4 minutes and 39 seconds, and the minimum average error associated with the test set was 0.0039. The interruption of the network's training occurred after 25,565 learning epochs. An epoch is a complete pass through the network of the entire set of training examples (NeuroShell 2). The training of the network was carried out for 50,000 and 100,000 epochs successively and no improvement was observed.

A network using GRNN (general regression neural network) paradigm was trained for the same data for comparison. The GRNN network outperformed the network trained with backpropagation and was, accordingly, adopted for the proposed cost model.

3.4.2 Structure Estimate

This model is designed to generate cost estimates for the structural framing of structural steel low-rise buildings (Moselhi and Siqueira 1998). A single-layer backpropagation architecture with 4 (four) nodes in the input layer (area, height, joist span and vertical loads) and 1 (one) node in the output layer (cost of the steel framing) was used for the neural network design. The number of nodes calculated by default, according to equation 1, is 8 (eight). Nine network models were developed, with the number of nodes in the hidden layer varying from 4 to 12, for the identification of the network structure with best performance. The input parameters were kept constant in all the nets. Table 6 shows the characteristics of the data used in the model development. The configuration of the 9 (nine) networks is described in Table 7. The network with 10 (ten) hidden nodes was selected as the one presenting better performance.

Table 6 Data Characteristics: Structural Steel Framing Cost NN

	Area (ft^2)	**Height (ft)**	**Joist Span (ft)**	**Vertical Loads (lbs/ft^2)**	**Structure \$ (\$)**
Minimum	2,040	12.50	20.60	41.90	6,258
Maximum.	73,186	33.00	75.00	85.20	217,746
Mean	14,400	20,50	38.70	67.40	39,885
Std Dev.	16,330	4.60	10.20	8.20	44,416

Table 7 Networks' Configurations: Structural Steel Framing

	N-4	N-5	N-6	N-7	N-8	N-9	N-10	N-11	N-12
Input nodes	4	4	4	4	4	4	4	4	4
Hidden nodes	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Output nodes	1	1	1	1	1	1	1	1	1

A network using GRNN paradigm was trained for the same data, for comparison. The GRNN network outperformed the network trained with backpropagation and was, accordingly, adopted for the proposed model.

3.4.3 Order of Magnitude Estimate

This neural network model provides the user a conceptual estimate of the direct cost of a building. The characteristics of the training data are shown in Table 8. A single layer backpropagation architecture with 4 (four) nodes in the input layer and 1 (one) node in the output layer was used in the design of the model. The number of nodes in the hidden layer, calculated by default according to the equation 1, is 8 (eight). Nine network models were developed, with the number of nodes in the hidden layer varying from 4 to 12 for the identification of the network's structure with the best performance. The input and output parameters were kept constant in all the nets. The configuration (i.e. structure) of the 9 (nine) networks is described in Table 9. The selected network contained 12 (twelve) nodes in the hidden layer.

Table 8 Data Characteristics: OM Total Cost NN

	Area (ft^2)	**Perim** (ft)	**Height** (ft)	**Joist Span** (ft)	**Total $** ($)
Min	2040.00	129	12.50	20.60	27,424
Max.	73,185.67	1,307	33.00	75.00	395,764
Mean	14,393.31	398	20,39	39,10	105,816
Std Dev.	16,329.09	272	4.58	9.90	87,738

Table 9 Networks' Configurations: OM Total Cost

	N-4	N-5	N-6	N-7	N-8	N-9	N-10	N-11	N-12
Input nodes	4	4	4	4	4	4	4	4	4
Hidden nodes	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Output nodes	1	1	1	1	1	1	1	1	1

A network using GRNN paradigm was trained for the same data, for comparison. The GRNN network outperformed the network trained with backpropagation. Accordingly, the GRNN network was selected.

Networks using outputs from wall and structure models and the total number of input parameters used to describe a building were also developed using backpropagation and GRNN paradigms for comparison of accuracy (Siqueira and Moselhi 1998a). NNSUB used cost predicted by best wall and structure neural network models as input parameters for estimating the total direct cost of a building. NNGAL used a total of 13 (thirteen) parameters as input for estimating the total direct cost of a building. The models are described in Table 10.

Table 10 NNSUB & NNGAL: Developed NNs

	NEURAL NETWORK MODELS	
	NNSUB (GRNN)	NNGAL (BPNN)
INPUTS		
Area		●
Height		●
Joist Span		●
Vertical Loads		●
Perimeter		●
Panel Height		●
Lateral Load		●
Wall Type		●
Canopy Area		●
Canopy Length		●
# Door		●
# Windows		●
% Openings		●
$ Wall	●	
$ Structure	●	
OUTPUT		
$ OM Total	●	●

The NNSUB trained with GRNN paradigm was selected amongst its category while the NNGAL trained with backpropagation (BPNN), 12 nodes in the hidden layer, outperformed in its category. The OM (Order of Magnitude) model outperformed the NNSUB and NNGAL models in the estimating of the total cost of the building. Eighty nine percent of the cases predicted by the OM model were within 20% error, while the NNSUB and the NNGAL models presented respectively 86% and 67% considering the entire data set.

For the projects unseen during training (contained in the production set) the percentage of the data within 20% error was of 71%, 43% and 71% respectively for the OM, NNSUB, and NNGAL models. Accordingly, the OM model was selected for total cost estimating of the buildings. Tables 11 and 12 describe performance of trained networks for pattern and production sets, respectively. Table 13 presents the results of the trained networks for the projects found in the production set.

Table 11 OM vs SUB vs GAL: Pattern Set

PATTERN SET	OM TOTAL	NNSUB	NNGAL
R squared	0.99	0.99	0.96
Mean absolute error	6.56	7.89	17.22
% within 5%	55.55	52.77	22.22
% within 5% to 10%	25.00	16.66	19.44
% within 10% to 20%	8.33	16.66	25.00
% within 20% to 30%	11.11	8.33	13.88
% over 30%	0.00	5.55	19.44

Table 12 OM vs SUB vs GAL: Production Set

PRODUCTION SET	OM TOTAL	NNMSUB	NNGAL
Mean absolute error	13.15	18.41	13.15
% within 5%	28.57	28.57	28.57
% within 5% to 10%	28.57	14.28	28.57
% within 10% to 20%	14.28	0.00	14.28
% within 20% to 30%	28.57	42.85	14.28
% over 30%	0.00	14.28	14.28

Table 13 Networks' % Error vs Actual Cost

Project (ft^2)	Cost ($)				% Error		
	Actual	OM	SUB	GAL	OM	SUB	GAL
15,000	94,455	112,434	114639	98411	19.03	21.37	4.19
9,880	75,920	72,223	55690	83940	4.86	-26.65	10.56
9,770	124,298	114,427	127880	123185	7.94	2.88	-0.90
9,600	77,727	75,666	71006	85069	2.65	-8.65	9.45
7,585	90,458	65,770	114741	96966	-27.29	26.84	7.19
2,759	40,075	49,323	52350	70279	23.08	30.63	75.37
2,040	33,000	30,623	32934	39991	7.20	-0.20	21.19

Tables 14, 15, 16 and 17 illustrate, respectively, the performance of selected network models used in the developed system. The order of magnitude model shows excellent results for the entire data set. The model performs similarly well for the cases unseen during the training of the network. The mean absolute percentage error calculated for the production set is 13%. The network model for the cost estimating of wall panels presents similar results, with a mean absolute percentage error of 17%. The parametric model for structural steel framing supports literature findings, showing poor performance for project cases with parameters outside the range for which the network has been trained.

The mean absolute percentage error calculated for this model, for the unseen project cases, is of 42%. An analysis of the project cases pertaining to the production set revealed that three out of the seven cases unseen during the training of the network presented parameters considerably out of the range of those used in the training set. The randomly selection of the data sets may account for such performance. As such, the model for the cost estimating of the structural steel framing needs further training with the inclusion of project cases with a wider range of values for the parameters considered.

Performance of developed neural network models against actual costs is illustrated in figures 11, 12 and 13.

Table 14 Performance of Developed Networks: Pattern Set

PATTERN SET	OM TOTAL	STRUCTURE	WALL
R squared	0.99	0.99	0.94
Mean absolute error	6.56	13.19	12.40
% within 5%	55.55	44.44	41.67
% within 5% to 10%	25.00	13.88	19.44
% within 10% to 20%	8.33	25.00	16.66
% within 20% to 30%	11.11	8.33	13.88
% over 30%	0	8.33	8.33

Table 15 Performance of the Developed Networks: Training Set

TRAINING SET	OM TOTAL	STRUCTURE	WALL
Mean absolute error	3.74	6.28	8.71
% within 5%	68.18	54.54	59.09
% within 5% to 10%	27.27	13.63	13.64
% within 10% to 20%	0.00	27.27	13.64
% within 20% to 30%	4.55	4.54	9.09
% over 30%	0.00	0.00	4.54

Table 16 Performance of the Developed Networks: Test Set

TEST SET	OM	STRUCT	WALL
Mean absolute error	8.82	3.19	18.65
% within 5%	42.85	57.14	14.28
% within 5% to 10%	14.28	14.28	28.57
% within 10% to 20%	28.57	28.57	0.00
% within 20% to 30%	14.286	0.00	42.85
% over 30%	0.00	0.00	14.28

Table 17 Performance of the Developed Networks: Production Set

PRODUCTION SET	OM	STRUCT	WALL
Mean absolute error	13.15	15.42	17.72
% within 5%	28.57	0.00	14.28
% within 5% to 10%	28.57	14.28	28.57
% within 10% to 20%	14.28	14.28	42.85
% within 20% to 30%	28.57	28.57	0.00
% over 30%	0.00	42.85	14.28

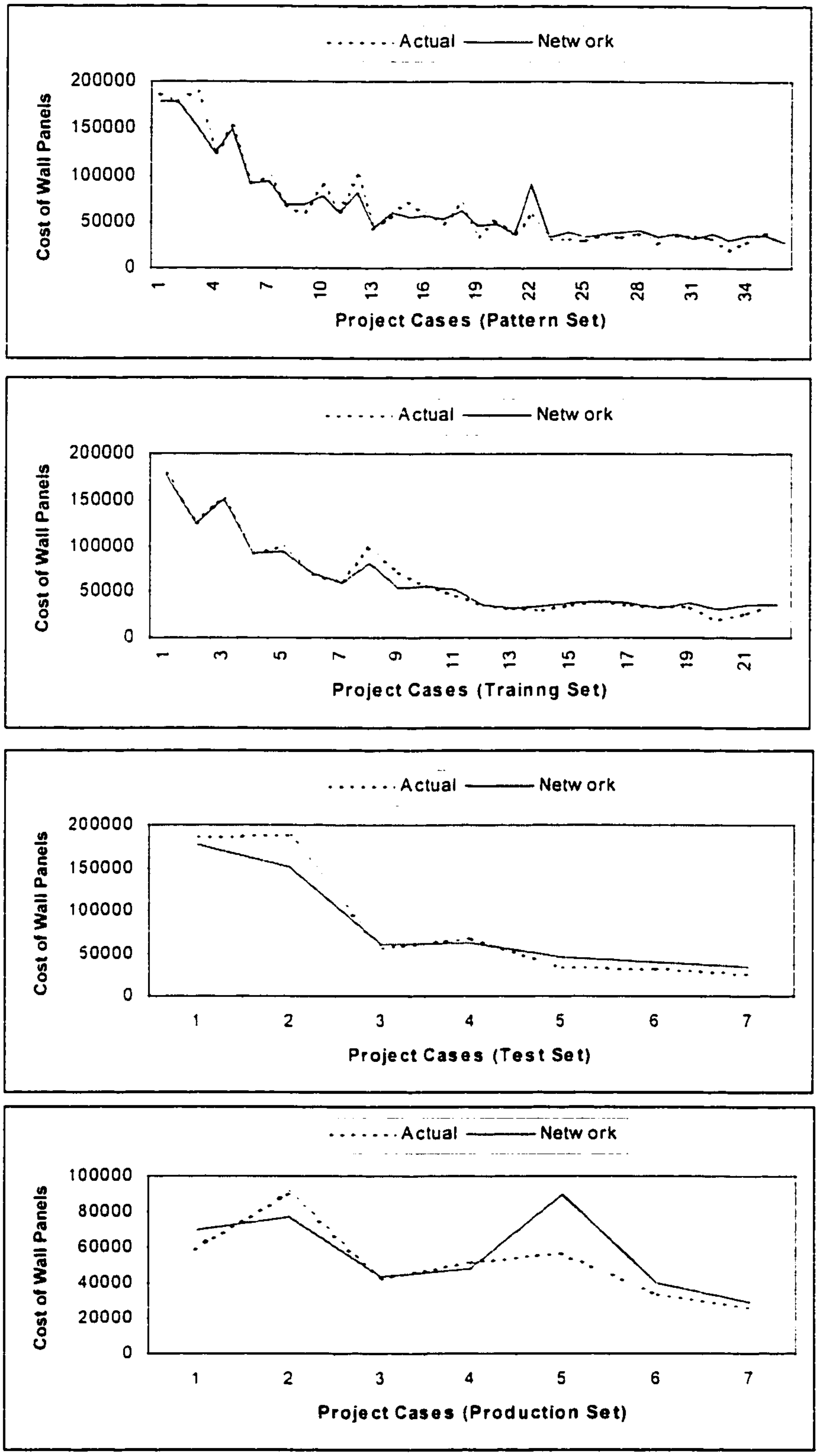

Figure 11 Performance of Wall Panels Cost NN

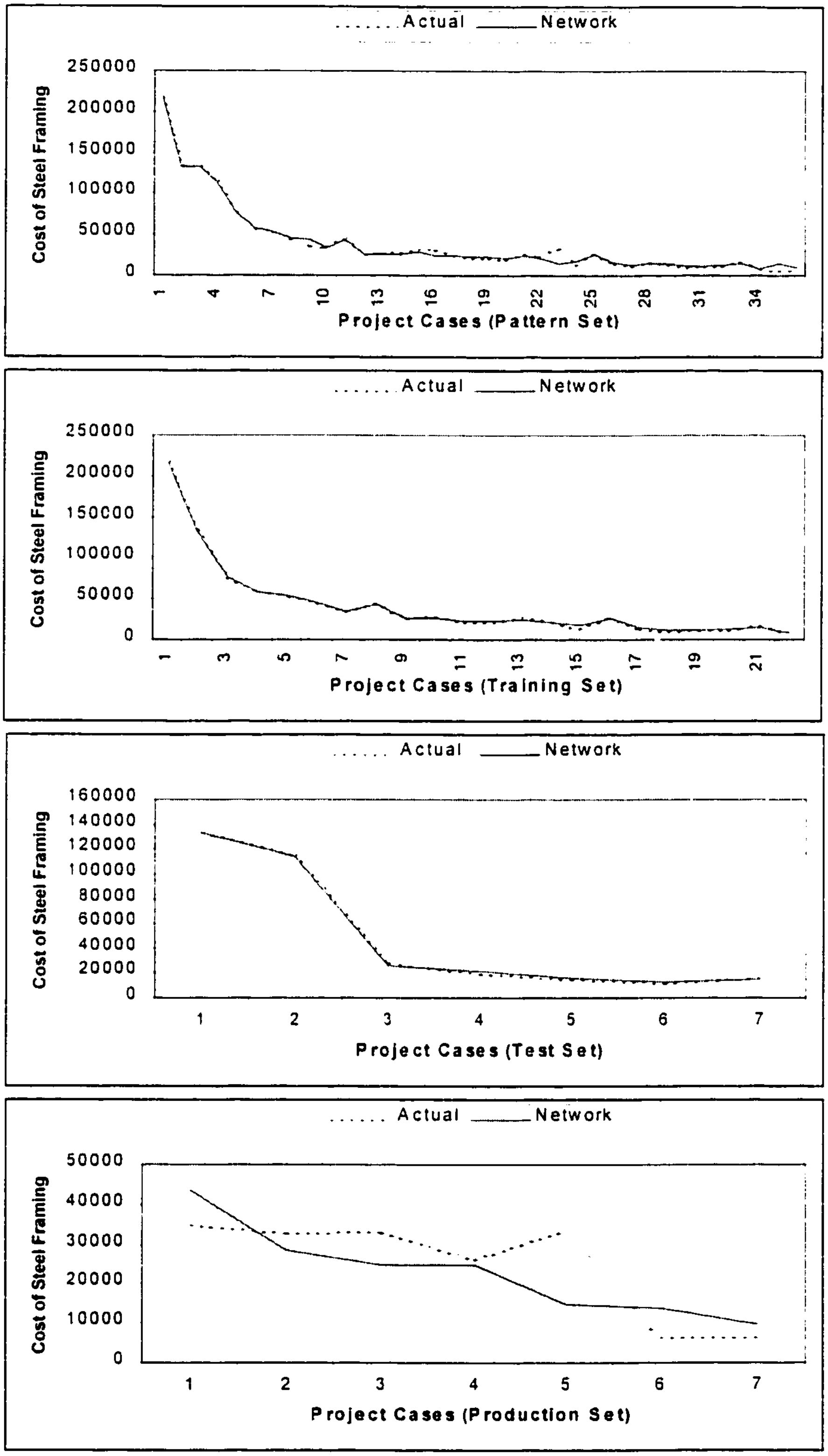

Figure 12 Performance Structural Steel Framing NN

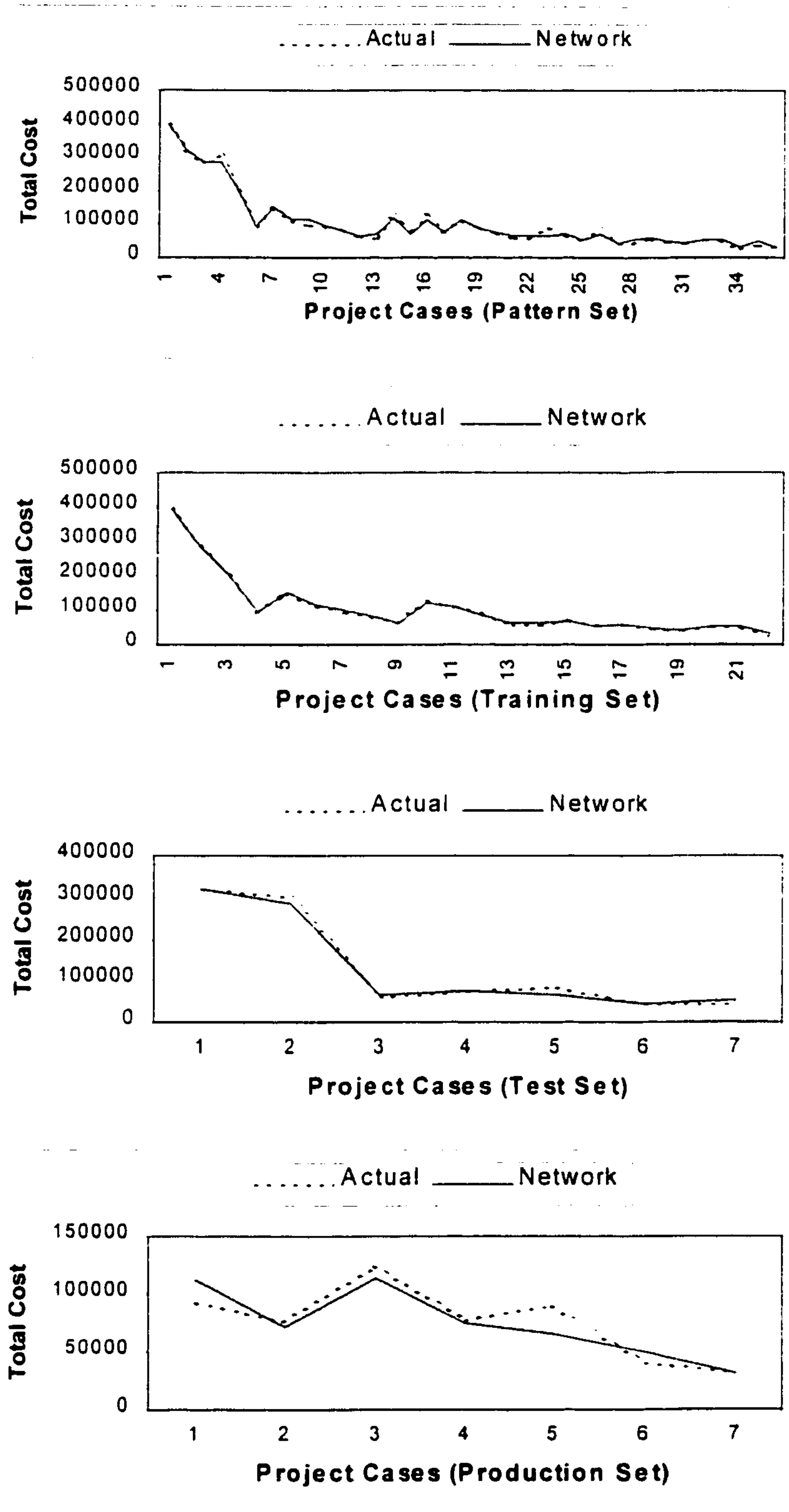

Figure 13 Performance of OM Total Cost NN

3.5 Testing and Evaluation

3.5.1 Neural Network Models

The testing and evaluation procedures of the neural network models consist of running the cost estimating models for projects for which the actual costs are known, but had not been presented to the models during training. These projects must have been previously analyzed for data appropriateness, since they will verify the problems the models can address. Projects with a wide range of parameter values are used in testing the models in order to ensure that the models are trained for the various possible expected estimating situations. The predicted costs are then compared to actual costs and the percentage error, accordingly, calculated.

As new buildings were completed, data were extracted and analyzed. If input parameters were found within the ranges for which the models were trained, the projects were selected. The corresponding data of selected projects were then input into the cost models and trained networks recalled. Predicted costs were compared to actual costs and differences analyzed, for evaluation of the models.

3.5.2 Regression

A regression analysis was performed for the project cases used in the training of the network models. This was performed using MS Excel environment. For comparison purposes, it was used to predict the cost of the project cases contained in the production set (unseen by the network during training). The results of the three developed models, for the seven project cases contained in the production set, are summarized in Tables 18, 19 and 20. Reg_1 represents the regression with least error, while Reg_2 was developed accounting for the same parameters as the developed networks. It should be noted that regression considering same parameters as trained networks presented considerably poor results, as in the case of wall panels cost estimating.

For the cost estimating of structural steel framing, regression performed better than the network model for the data contained in the production set: the mean absolute percentage error was equal to 20% and 42% respectively. A comparison considering the entire data set, on the other hand, showed that the neural network model outperformed regression. The mean absolute error calculated for the neural network model and the regression equation were 11% and 15%, respectively. This could be attributed to the randomly selection of the data sets, particularly those in the production set having parameters considerably out of the range used in training.

For the two other models, total direct cost and cost of wall panels, neural network models clearly outperformed regression developed for the same parameters as the networks, with mean absolute percentage error for the respective production sets equal to 13% vs 21% and 18% vs 57%.

Table 18 Performance of OMNN vs Regression

Project (ft^2)	Cost ($)				% Error		
	Actual	NN	Reg_1	Reg_2	NN	Reg_1	Reg_2
15,000	94,455	112,434	100,579	112,991	19.03	6.48	19.62
9,880	75,920	72,223	83,562	92,235	4.86	10.06	21.49
9,770	124,298	114,427	107,789	106,945	7.94	-13.28	-13.96
9,600	77,727	75,666	82,359	90,655	2.65	5.95	16.63
7,585	90,458	65,770	106,908	103,475	-27.29	18.18	14.39
2,759	40,075	49,323	48,656	58,244	23.08	21.41	45.34
2,040	33,000	30,623	20,826	39,169	7.20	-36.89	18.69

R_1 - best regression (least error)
R_2 - using same parameters as neural network

Table 19 Performance of WallNN vs Regression

Project (ft^2)	Cost ($)				% Error		
	Actual	NN	Reg_1	Reg_2	NN	Reg_1	Reg_2
15,000	59,484	69,756	73,508	37,481	17.27	23.57	-36.99
9,880	40,012	44,024	66,575	64,267	2.35	54.78	49.42
9,770	91,125	77,336	85,406	100,276	-15.13	-6.28	10.04
9,600	51,521	48,268	52,862	65,828	-6.31	2.60	27.77
7,585	56,909	89,936	70,561	91,263	58.04	23.99	60.37
2,759	33,700	39,675	42,243	62,882	17.73	25.35	86.59
2,040	26,741	28,677	12,506	-8,016	7.24	-53.23	-129.98

R_1 - best regression (least error)
R_2 - using same parameters as neural network

Table 20 Performance of StructNN vs Regression

Project (ft^2)	Cost ($)				% Error		
	Actual	NN	Reg_1	Reg_2	NN	Reg_1	Reg_2
15,000	34,971	43,737	41,063	40,531	-25.06	17.42	15,90
9,880	32,908	28,666	27,270	26,725	-12.10	-17.13	-18.79
9,770	33,173	24,846	26,974	27,124	-25.10	-18.68	-18.23
9,600	26,206	24,882	26,516	26,638	-5.05	1.18	1.65
7,585	33,550	14,738	21,087	23,427	-56.07	-37.14	-30.17
2,759	6,427	13,909	8,087	6,179	116.42	25.82	-3.85
2,040	6,258	9,733	6,150	3,075	55.53	-1.72	-50.86

R_1 - best regression (least error)
R_2 - using same parameters as neural network

3.7 Summary

In this chapter neural network was discussed as a tool that can be used for reducing cost and time in the cost estimating process. The criticality of preparing high quality data for the development of neural network models has been established. Three neural network models have been designed and trained for direct cost estimating: order of magnitude, parametric wall and parametric structure. The trained models were tested and their accuracy evaluated when presented to new project cases. The validity of the models is supported by the performance observed on a number of completed projects. Regression was also performed for comparison purposes and was found to corroborate literature findings. It has been demonstrated that the developed system can predict costs with a reasonable degree of accuracy when the project being estimated has its parameters' values within the ranges for which the system has been trained.

Overall results suggest that neural network is a powerful tool for producing credible conceptual cost estimates, at a predesign stage, based on the company's knowledge and experience. Neural network moves cost considerations to the predesign stage, where the greatest benefits can be derived. Principal benefits include determining the near optimum configuration of design parameters for cost, while saving considerable time and resources in the estimating process. As such, this system helps not only in the go/no-go decisions but also in the checking of detailed cost estimates prior to bid submittals.

CHAPTER 4 - DEVELOPED AUTOMATED COST ESTIMATING SYSTEM

4.1 General

Parametric cost estimating is used to assist in decision-making, particularly during planning and bid preparation stages. Assumptions over future cost and how they relate to the scope and characteristics of the project must be made in a timely manner, while considering a number of variables. This type of estimating is most useful for cost and value evaluations early in the project life cycle when not much is known about the project scope.

For a building rather "similar" to a previously fabricated one, a mere analogy may seem enough. However, in current competitive and fast moving environment, such situation does not occur very often. Primarily in case of low-rise structural steel buildings, cost models based upon previously fabricated buildings should account for a number of variables. Such models shall allow for cost and time effective evaluation of 'what if' scenarios, where a number of project alternatives can be assessed, throughout planning and bidding stages, translating a project's quantitative and/or qualitative data (parameters) into cost.

Neural networks are being increasingly used as a tool for modeling cost, (Hegazy and Ayed 1998, Bode 1998, Adeli and Wu 1998, Creese and Li 1995, de la Garza and Rouhana 1995, McKim 1993) although performance of neural network models is usually limited to certain ranges of parameter input values. This thesis proposes a neural network based cost estimating system (ACE). The proposed system utilizes three neural network models, one for the prediction of the total direct cost of the building, one for the prediction of the cost of the structural steel framing of the building and a third one for the prediction of the cost of building's wall panels. These models were designed based on the industry needs and follow the major element classification of UNIFORMAT II (Bowen et al. 1992), commonly used for parametric building cost evaluations.

ACE aims at re-designing current cost estimating process in order to make it more efficient. ACE generates conceptual cost estimates using the values for specific parameters, which describe the project. The user can start a new estimate by simply selecting a type of estimate and then inputting requested values of the project parameters. The system automatically estimates the direct cost of new project. Subsequent windows allow for cost adjustments and allocation of markups and taxes.

The use of the proposed system reduces the cost estimating process to easily retrievable information found in the system-generated reports: project description, estimated direct cost, cost adjustments, allocation of markups and taxes and total project cost. The design of specific windows for cost prediction, cost adjustments, and allocation of markups and taxes simplifies data entry. As such, the trained models help not only to preserve the company's estimating knowledge, but also to apply this same knowledge in the generation of new cost estimates.

4.2 System Requirements

The system is required to:

1) Benefit from experience gained on past projects. This includes actual cost incurred on material, labor and subcontractors,
2) Meet required accuracy, while being practical and user-friendly,
3) Integrate different estimating phases, reflecting current estimating practices and industry's domain knowledge, and
4) Promote cost and resource savings, supporting the user on the capitalization of more business opportunities.

4.3 System Description

The system is designed and coded in Borland C++ 5.0 to integrate diverse phases of the cost estimating process: direct cost estimating, cost adjustments, allocation of markups and taxes and cost related reporting phases (Siqueira 1999). It integrates artificial intelligence technologies and traditional spreadsheet applications (see Figure 14).

The system runs on a 166MHz Windows™ compatible computer with 64 MB of RAM. We suggest a 100MHz or faster computer with a minimum of 32 MB of RAM; 150 MB of available hard disk storage; Windows 95 (or later); and a mouse.

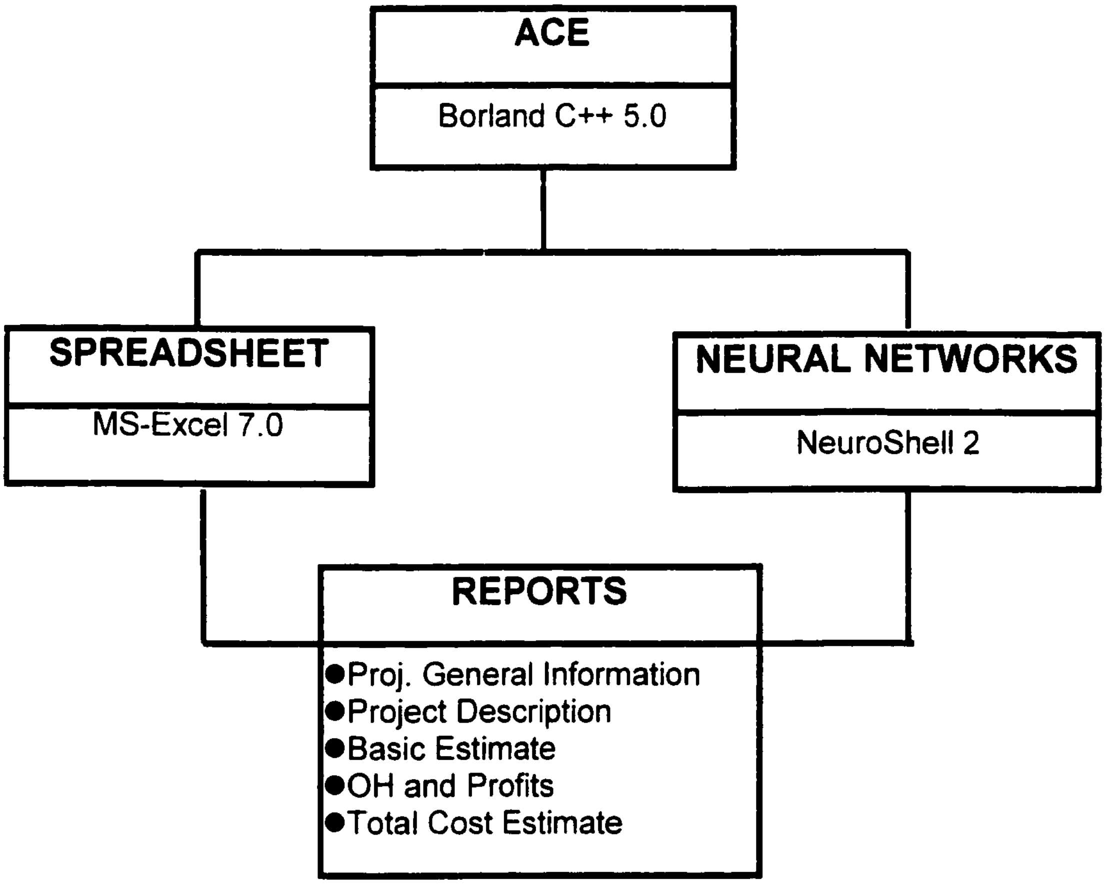

Figure 14 ACE Automated Cost Estimating System

ACE incorporates three neural-network cost models, as described in Section 3.3: 1) Order of magnitude, 2) Parametric cost estimating of walls and 3) Parametric cost estimating of structural steel framing.

Screens for data input parameters were designed for each one of the models (See Figure 15). Each screen identifies the main parameters impacting cost for the selected type of estimate, activating this way the corresponding neural-network cost model.

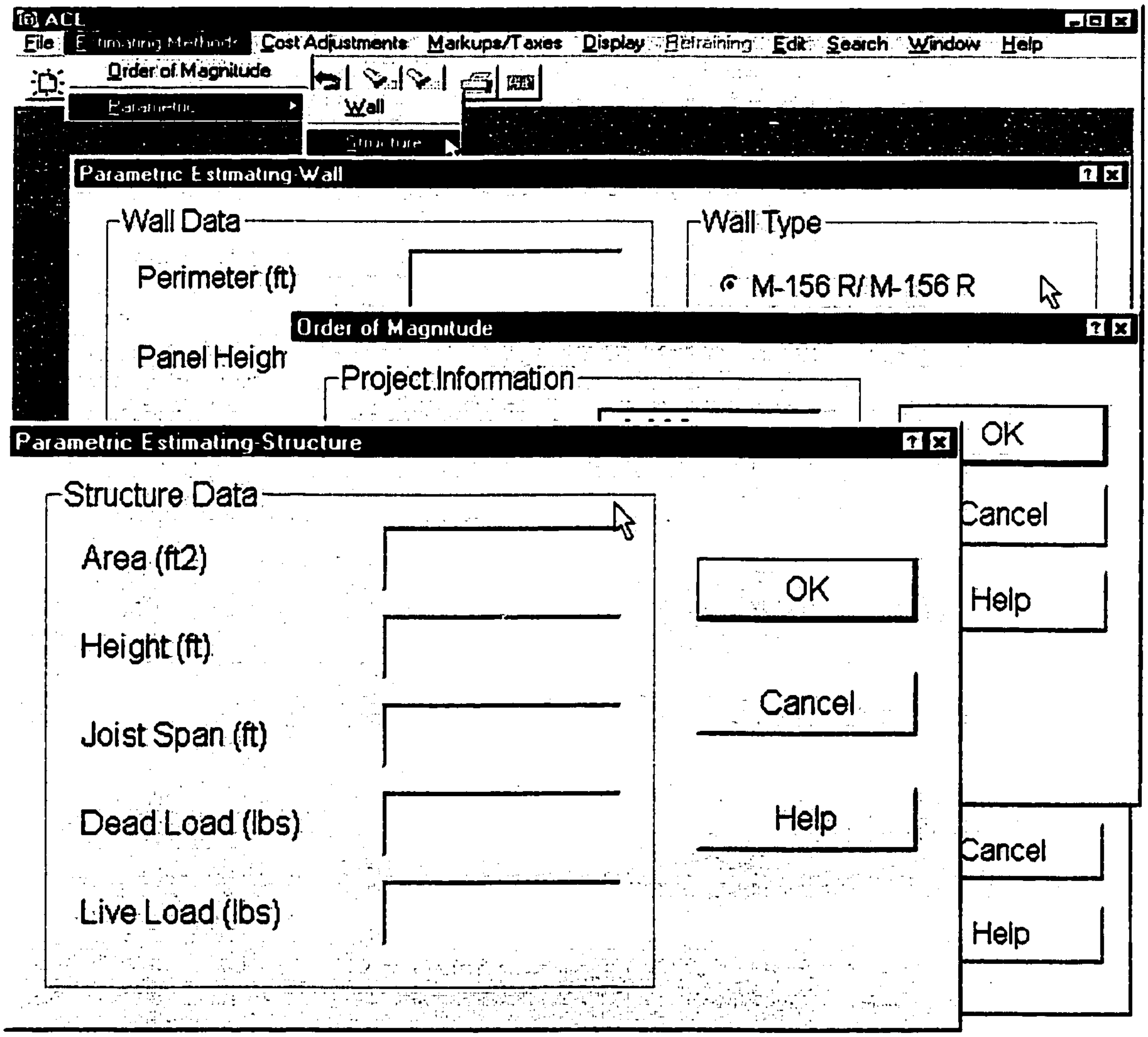

Figure 15 Automated Cost Estimating System

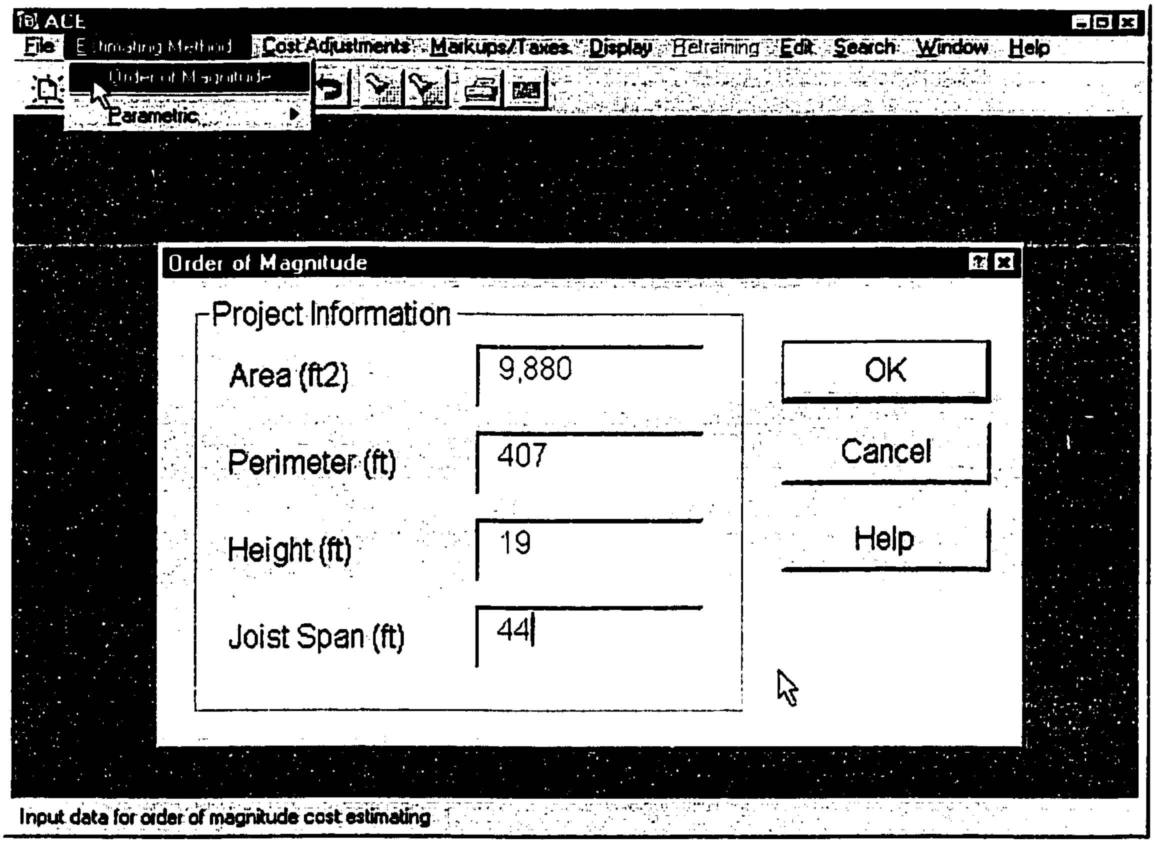

Figure 16 Order of Magnitude Estimate

The input screen for the Order of magnitude type estimate allows the user to specify the: building floor area, perimeter, building height, and joist span. ACE then estimates the total direct cost of the building. Once the data is keyed in, ACE estimates the total cost of the building.

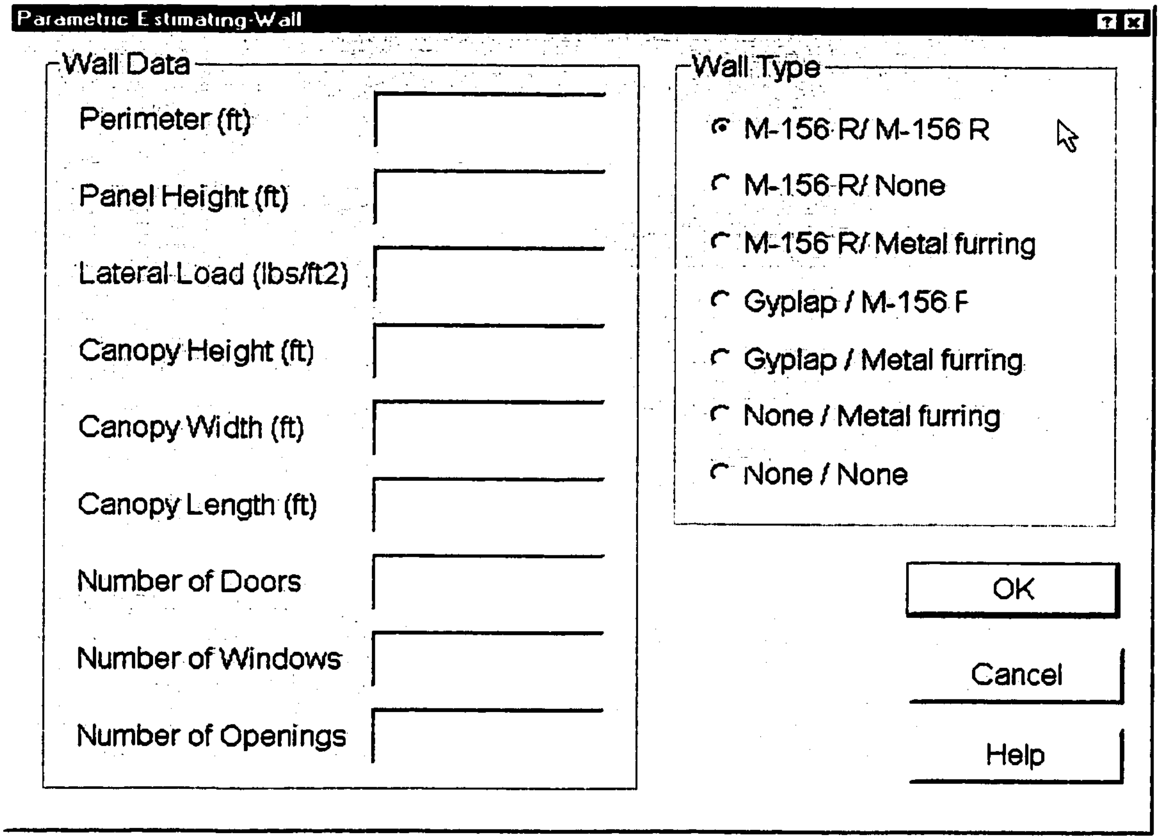

Figure 17 Parametric Wall Estimate

The Parametric Wall screen (see Figure 17) incorporates data input for: perimeter, panel height, lateral loads, canopy height, width and length, number of doors, windows and openings. After the user keys the data in, ACE estimates the cost of wall panels.

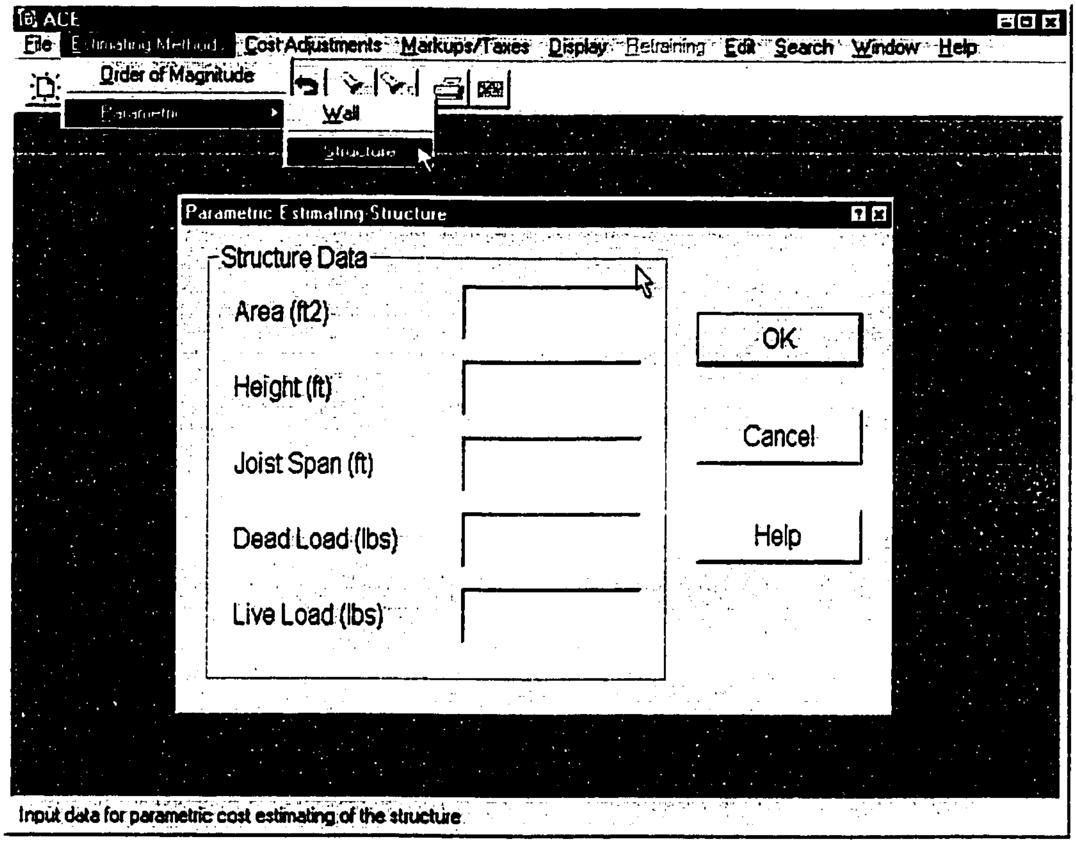

Figure 18 Parametric Structure Estimate

The Parametric Structure screen (Figure 18) incorporates data input facilities for: building floor area, building height, joist span, and vertical loads. ACE estimates the cost of steel framing after the requested data is keyed in.

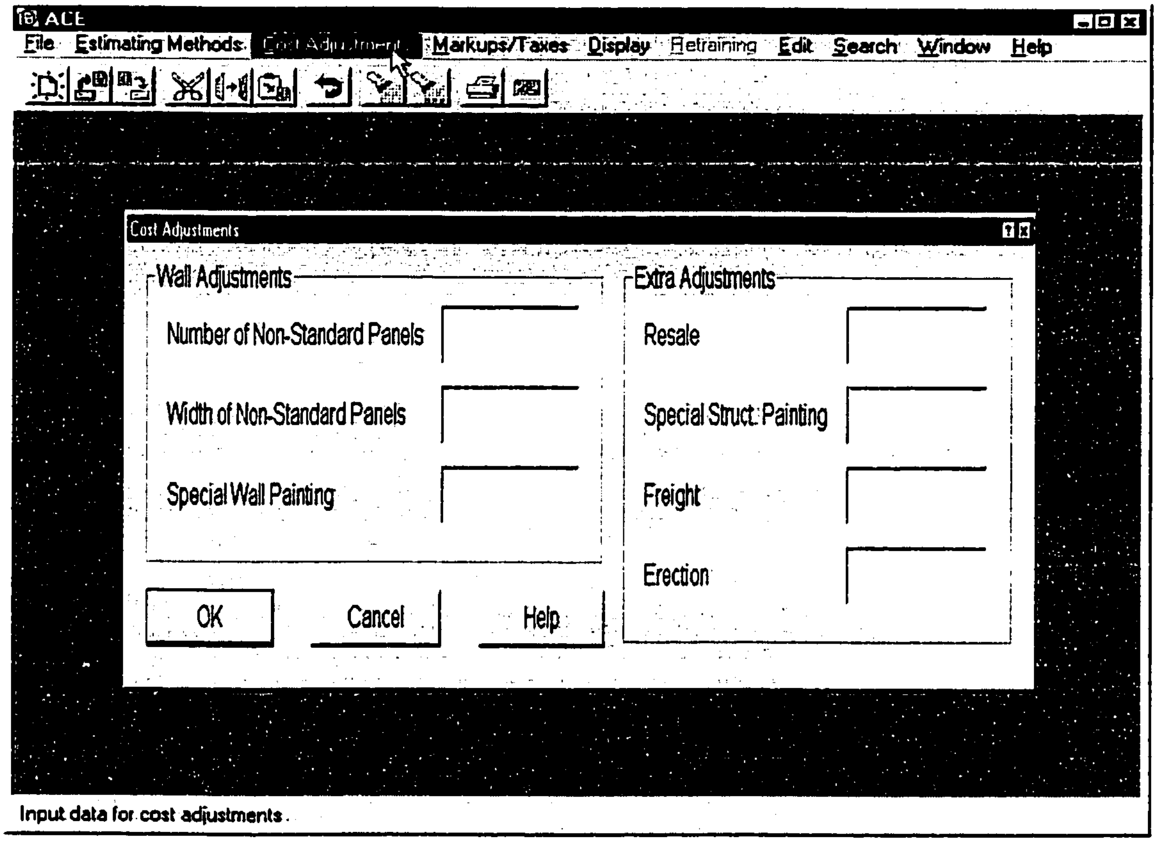

Figure 19 Cost Adjustments

A screen for cost adjustments was designed for data input facilities. Once the information is provided, ACE will make the requested adjustments.

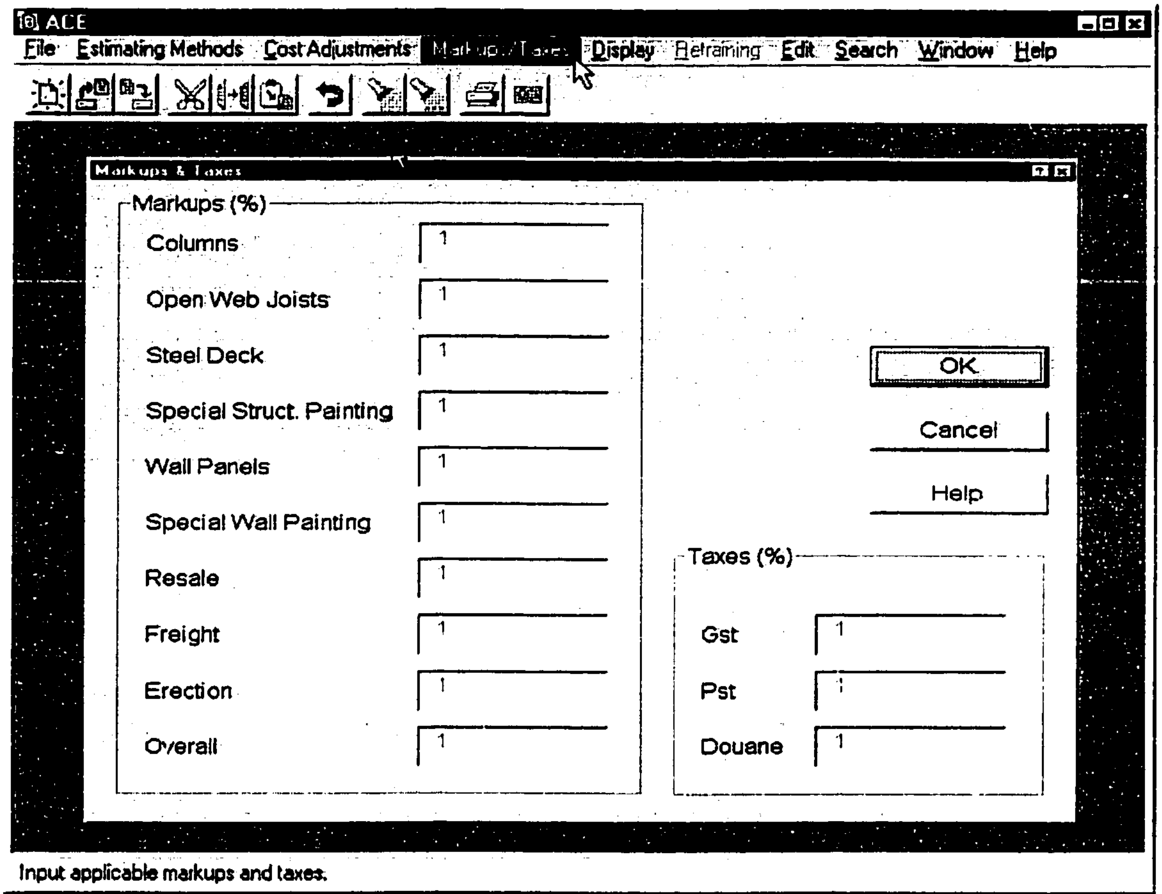

Figure 20 Markups & Taxes

The markups and taxes input screen is designed to facilitate the allocation of different markups to individual cost items, such as: columns, joists, steel deck, wall panels, special painting for the steel framing, special painting for the wall panels, resale, freight and erection; as well as the allocation of an overall markup, to cover risk and overall market conditions. The screen also facilitates the allocation of federal and provincial sales taxes (GST and PST), and customs in case of exporting is also included.

The cost report is presented in two major sections. A section displaying project information, such as project name, number and address, client's name, address and person for contact, date and place of project delivery, project's physical characteristics and so on. As the other major section are the cost-related reports, describing the value of the basic estimates, estimated OH and profits along with percentage markup allocated, and the total cost of the project, including provincial and federal taxes. The provided cost breakdown feature facilitates project cost analysis as a function of assigned values to project parameters.

ACE is designed to, upon request, automatically produce cost-related reports for the building being estimated. All relevant data is transferred into the quotation forms (also known as bid proposals). The Project General Information screen provides fields to record estimate information pertinent to user's practice. Once the estimate is generated, users can then verify project specifications and predicted cost, analyzing then different project alternatives. Cost improvements can then be determined.

4.4 Example Application

In order to demonstrate the capabilities of ACE and its performance, a real project example is selected and its input parameters extracted (Siqueira 1999). The selected building was constructed in Ville D'Anjou, Quebec, Canada, with a total floor area of 9,880ft^2. The examination of blueprints and documents pertaining to this project provided the following parameters: total perimeter length of 407ft, height of 19ft, joist span of 44.2ft, vertical loads of 70lbs/ft^2, and lateral load of 7.7 lbs/ft^2. The actual direct cost of this job, indexed to January 1997, was $75,920. All of these values are within the range used in the training of the networks. The estimating process is initiated by the selection of a type of estimate. ACE's menu provides two options for the type of estimate: order of magnitude and parametric. The first option is selected for the example application. This option requires the entry of four input parameters: area, height, joist span, and perimeter (see Figure 12). Following that, the respective neural network model is recalled, and the direct cost based on these four parameters is predicted.

ACE estimates the direct cost for this project to be $72,233.00, while the actual direct cost of the project was $75,920.00. The absolute error calculated for this case is of 5%. It should be noted that only the direct cost is calculated for this project example. The system is capable of predicting the total cost of the project upon keying in the markup corresponding to market conditions. As well, various reports concerning the project itself and the cost estimating process may be provided upon request. Based on such reports, a new cost estimate may be generated for different project scenarios or alternatives in order to meet the user's needs. It can be achieved by just changing the values for the input parameters.

4.5 System's Limitations and Potential Applications

The system can best be used to predict the cost of projects which have input parameters within the range for which the neural network models were trained.

Database must be updated and neural network models retrained to account for new cases. This is not only important to continue building on the experience gained on projects completed but also to account for improved technology and/or change in material cost.

The model is applicable to low-rise structural steel commercial/industrial buildings. This includes offices, warehouses, industrial buildings, and labs. It does not apply to residential or wood construction. It provides the cost of the building shell, i.e. superstructure (structural steel framing) and exterior closure (exterior walls, windows, exterior doors and openings).

The neural network methodology described for cost estimating in this thesis can readily be applied in other domains in construction management where traditional algorithmic tools may prove inadequate (Siqueira 1999). It is suitable for modeling problems involving quantitative and qualitative factors, with a domain rich in historical examples. It can be applied in risk management and productivity models. A thorough analysis of the above mentioned potential applications can reveal the main parameters to be used in the generation of each neural network model.

By identifying the parameters giving rise to risk in a project, and correlating them to the risk encountered, one can develop a model for assessing and quantifying the risk involved. In a way, the values assigned to these parameters, whether quantitative or qualitative, describe a pattern that could easily be associated with the risk encountered from available project records. These project patterns and their associated level of risk can be used to train a neural network in a similar way to that described earlier in this thesis. For example, in the delivery of EPC (Engineering, Procurement and Construction) projects the following factors could be used to describe the patterns depicting the risk environment associated with these projects: 1) project location, 2) project complexity, 3) delivery system (fast-track or traditional), 4) state of technology utilized, 5) procurement plans and policies, etc. (Moselhi 1997, PMBOK 1996, Moselhi et al 1993).

With respect to productivity models, similarly, one can generate a pattern (i.e. a set of governing factors) that depicts the project's environment and associate it with actual productivity levels attained on those projects. And accordingly develop a suitable neural network model. Again, for EPC projects, the parameters impacting productivity may include: 1) frequency of change orders, 2) intensity of design errors and omissions, 3) design changes, 4) complexity of work, 5) % of unbalanced crews, 6) unbalancing of successive operations, 7) management effectiveness, etc. (AbouRizk and Portas 1997, Moselhi et al. 1991a, Neil and Knack 1984).

These models can be used for project planning, procurement and control, creating standards throughout the company. As well, these models can capture and build on the company's experience and, as such, grow with the company adapting to its dynamically changing business strategy. In general, the type of neural networks described in this thesis can be used to develop a number of decision support systems to assist in various management functions.

CHAPTER 5 – SUMMARY AND CONCLUDING REMARKS

5.1 Summary

The problem of project cost estimating, at a predesign stage, for low-rise structural-steel buildings has been studied and the limitations of current practice have been identified. The nature and the complexity of this problem have rendered themselves to be best dealt with detailed estimates. Detailed estimates, however, have been proven inadequate in responding in a timely manner to market needs. Conceptual cost estimates, although seen as a solution, are difficult to generate for this type of buildings. The major limitation associated with that technique can be attributed to a number of variables to be considered in parallel and, as consequence, the estimator's inability to apply industry specific knowledge.

To overcome the above shortcomings, a structured methodology for cost estimating of low-rise structural-steel commercial and industrial buildings is developed to enable estimating, design and management teams prepare practical and timely cost estimates. The methodology uses conceptual cost estimates, at a predesign stage, to determine the main design parameters of a building prior to detailed cost estimating. This enables efficient estimating of direct costs, incorporating the impact of significant project parameters. Input parameters are therefore determined by selecting the optimized set having impact on the overall project direct cost.

The methodology further integrates efficient direct cost estimating neural network models, algorithms for cost adjustments and allocation of markups and taxes, and the generation of cost related reports. Neural networks are used to develop direct cost estimating models based on the company's experience. Cost adjustments and markup allocation and taxes are used to respond to market conditions. As such, cost estimates for different project alternatives can be used for assessing the impact of different input parameters on the cost of each of the generated alternatives.

The performance of the neural network models is tested against projects not seen during the training and also regression techniques. The results indicate that the proposed models statistically outperform the traditional regression techniques. In addition, the proposed models tends to generate more conservative cost estimates, which is desirable at this estimating level. Cost estimates performed using trained neural network models are very simple to generate. They do not, however, present reasoning as to how these estimates are generated.

A PC-based software system (ACE) is then developed to automate the conceptual cost estimating process, using the neural network models for direct cost estimating. The system is highly interactive, providing a user-friendly interface. It combines the advantages of automation and human input throughout the cost estimating process. This flexibility proves advantageous, yielding a number of solutions in a timely fashion.

Features of ACE allow for cost adjustment, markup allocations and the generation of cost related reports, illustrating the benefits of the system. It has been shown that the system can be used as a decision support tool for improving and facilitating the preparation of proposals for low-rise structural-steel commercial and industrial buildings. The fact that the system allows much flexibility in decision-making pertaining to cost adjustments, markup and tax allocation, and provides users with cost related reports for their own decision-making, may prove useful in generating optimal cost estimates, that satisfies owners' construction needs.

Cost estimates generated using ACE can be used in timely estimation of direct cost, in addition to the checking of detailed estimates prior to bid submittals. An example application is presented in an effort to illustrate the essential features of the system and demonstrate its effectiveness and practicality.

The apparent advantages of the proposed system over current cost estimating practice lie in the addition of a conceptual cost estimating stage at a predesign level to the estimating process. The generation of conceptual cost estimates at that level promotes adequate assessment of main design parameters prior to detailed estimating and successful generation of cost proposals. The procedures used within the system's four phases exhibit practical and fairly simple characteristics, capturing current cost estimating practice and providing a useful support for the development of reliable bid proposals.

This study, like others reported in the literature, supports the fact that neural networks are ideal for forecasting problems, such as the problem at hand. NNs learn by example, generalizing the knowledge used in their training in order to solve similar problems. Despite the difficulties generally associated with designing and training a neural network model for a particular problem, results show that those difficulties are outweighed by the performance of the models for the class of problems described. Guidelines provided in this study for data analysis, design, training and evaluation of the neural network models may be utilized in the development of new models for different applications, particularly those suited for the backpropagation and GRNN paradigms.

The developments made in this study with respect to conceptual cost estimating demonstrate the powerful generalization capabilities of neural networks. As opposed to regression techniques, the decision support system, developed in this study, has several interesting features and advantages:

1) It captures the experience gained on completed projects and utilize it to build the domain knowledge.
2) It provides a decision aid for cost estimating linking design parameters to project cost.

3) It has a user-friendly interface that facilitates the capturing of input parameters, cost adjustments and allocation of markups and taxes.
4) It facilitates integration of the project cost elements, stated in 3) above, providing a comprehensive proposal/bid document
5) It derives solutions instantaneously utilizing generalized knowledge acquired from actual projects.

The contributions of this study are:

1) Extensive analysis of the cost estimating environment of low-rise structural steel buildings
2) Development of a methodology to improve current cost estimating practice.
3) The development of neural network models for direct cost estimating at a predesign stage, overcoming the major limitations experienced in the cost estimation of low-rise structural-steel buildings.
4) The development of an automated cost estimating system for low-rise structural steel buildings, capturing current practice in a user-friendly environment. It provides a practical mean for estimating, design and management teams to respond to market needs in a timely manner. The development of ACE is expected to significantly improve the quality of the cost estimating process for this class of projects.

5.2 Future Work

This study has successfully demonstrated the feasibility of applying neural network techniques to conceptual cost estimating of low-rise structural-steel commercial and industrial buildings. However, the neural network methodology described in this thesis could readily be applied in other domains in construction management where traditional algorithmic tools may prove inadequate. It is suitable for modeling problems involving quantitative and qualitative factors, with a domain rich in historical examples. It can be applied in risk management and productivity models. A thorough analysis of the abcve mentioned potential applications can reveal the main parameters to be used in the generation of each neural network model.

These models can be used for project planning, procurement and control, creating standards throughout the company. As well, these models can capture and build on the company's experience and, as such, grow with the company and allow it to adapt its dynamically changing business strategy. In general, the type of neural networks described in this thesis can be used to develop a number of decision support systems to assist in various management functions.

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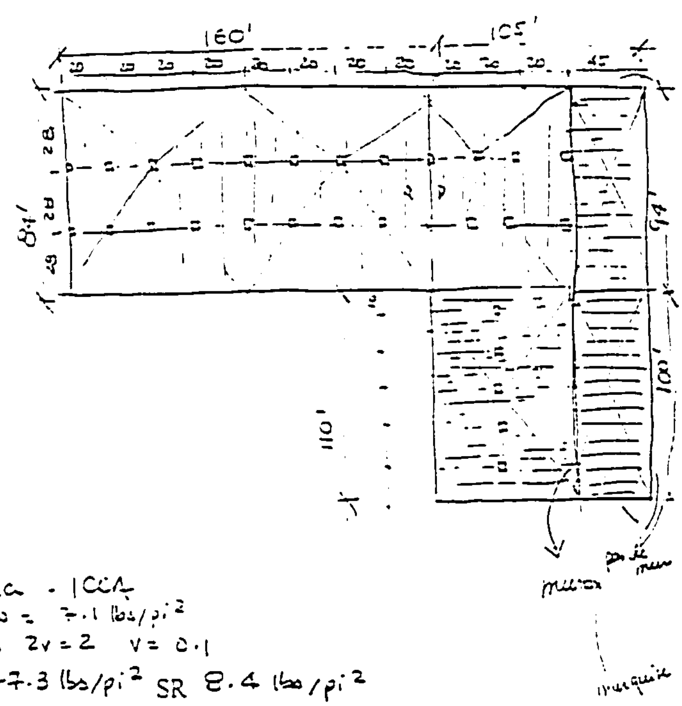
APPENDIX I DESIGNED DATA ENTRY SHEET

1- QUOTATION

1.1- Date ~~28/03/95~~ march 6 1996
1.2- Quotation number [redacted]
1.3- Project name [redacted]
1.4- Project address [redacted]
1.5- Customer
1.6- Address
1.7- Postal Code
1.8- Contact
1.9- Phone
1.10- Fax
1.11- Estimated Cost [redacted] Actual Cost [redacted]
1.12- Estimated Duration fin mai Actual Duration [redacted]

2- SYSTEM: MUROX



2.1- Width
2.2- Length
2.3- Top of steel 16'9"
2.4- Clear height 14'0"
2.5- Foundation wall elevation
2.6- Floor elevation
2.7- Joist span
2.8- Beam/truss span

3- LOADS

3.1- Applicable Code Canada - ICCA
3.2- Wind/seismic load q 1/30 = 7.1 lbs/pi² Za = 4 Zv = 2 v = 0.1
3.3- Snow load (ground) SS 77.3 lbs/pi² SR 8.4 lbs/pi²
(factors) Cb 0.8 Cw 0.75
3.4- Dead load 18 lbs/pi²
3.5- Live load 54.8 lbs/pi²

4- ROOF

4.1- **Steel deck:** P-3615 P-2436 P-2432 P-2438 P-1519

4.2- **Zinc coat:** LZC Galvanized

4.3- **Gauge** 16 18 20 22 28

5- WALL

5.1- **Exterior finish:** M-156R Gyplac None

5.2- **Exterior gauge:** 22 24 26 28

5.3- **Interior finish:** M-156R Metal furring Plywood None

5.4- **Interior gauge:** 20 22 24 26 28

5.5- **Air barrier:** Yes No

5.6- **Vapour barrier:** Yes No

5.7- **Insulation:** Yes No

6- ACCESSORIES

		Quantity	Dimensions	Surface
6.1-	**Door(s)**	7	3x7	
		1	6x7	
6.2-	**Window(s)**			
6.3-	**Opening(s)** wall -	4	(6x7)	
		6	(9' x 6')	
	roof	8	(2' x 2')	
6.4-	**Canopy(s)**			
	Cadre pour porte levante.	1	(9' x 10')	

7- ANNEX BUILDING

7.1- **Width**

7.2- **Length**

7.3- **Top of steel**

7.4- **Clear height**

7.5- **Foundation wall elevation**

7.6- **Floor elevation**

7.7- **Joist span**

8- MEZZANINE

- 8.1- Surface:
- 8.2- Live load:
- 8.3- Joist span(s):
- 8.4- Beam span(s):
- 8.5- Steel deck: P-3615
- 8.6- Zinc coat: LZC Galvanized
- 8.7- Gauge: 18 20 22

9- OVERHEAD CRANE

- 9.1- Type: Under Hung Top Running
- 9.2- Capacity:
- 9.3- Runway beam: ________ linear feet
- 9.4- Supply of rail: Yes No

10- COST/SCHEDULE BREAKDOWN Duration $ Cdn

10.1- Planning and Design

		Duration	$ Cdn
-Columns	________	53 hrs	[redacted]
-Joists	________	18 hrs	[redacted]
-Murox	________	319 hrs	[redacted]

10.2- Material

	Quantity	Total Weight	Duration	$ Cdn
-Columns	________	[redacted] lbs	59 hrs	[redacted]
-Joists	________	[redacted] lbs	285 hrs	[redacted]
-Steel deck	[redacted] lbs	________		[redacted]
-Panels	________			[redacted]

10.3- Fabrication of panels

		Duration	$ Cdn
-Panels	________	682 hrs	[redacted]

10.4- Transportation

		$ Cdn
-Structure+panels	________	[redacted]

10.5- Extra

APPENDIX II DATA SAMPLE

Case	Tota$-97	Area (ft^2)	Perim(ft)	Can A (ft2)	Can L (ft)	Height (ft)	PHeight (ft)	Jspan (ft)	Vload(lb/ft^2)
1	[redacted]	73186	974			20	20	30	59
2	[redacted]	58503	1307	30	323	19	19	38	57
3	[redacted]	49335	824	18	90	24	24	57	65
4	[redacted]	39200	858	31	108	28	27	50	64
5	[redacted]	33810	828			17	17	32	73
6	[redacted]	21366	180	5	24	17	17	30	70
7	[redacted]	16875	520			29	29	75	66
8	[redacted]	16000	520	8	10	17	17	40	79
9	[redacted]	15000	500			16	16	33	65
10	[redacted]	13910	440			22	19	33	60
11	[redacted]	12553	135	6	77	18	18	46	85
12	[redacted]	11150	270			14	14	30	74
13	[redacted]	10394	293			15	15	34	69
14	[redacted]	10000	410	6	60	23	23	40	59
15	[redacted]	9880	407			19	19	44	70
16	[redacted]	9770	459			26	24	52	81
17	[redacted]	9600	280			22	22	40	68
18	[redacted]	9032	725			25	21	33	68
19	[redacted]	8771	396	5	22	16	16	43	70

Data Sample