Estimating Labor Production Rates for Industrial Construction Activities

By S. AbouRizk,[1] P. Knowles,[2] and U. R. Hermann[3]

Abstract: This paper discusses an approach based on artificial neural networks that enables an estimator to produce accurate labor production rates (labor/unit) for industrial construction tasks such as welding and pipe installation. The paper first reviews factors that were found to affect labor production rates on industrial construction tasks, current estimating practices and their limitations, and the process followed in collecting historical production rates. An artificial neural network model is then described. The model is composed of a two-stage artificial neural network, which is used to predict an efficiency multiplier (an index) based on input factors identified by the user. The multiplier is then used to adjust an average production rate given in man-hours/unit for use on a specific project. Estimates of production rates from the new approach are compared to the existing estimating practices and conclusions are presented.

INTRODUCTION

Detailed estimation of construction costs involves determining quantities of work to be completed and the associated costs. There are generally two methods of cost determination: unit pricing and resource enumeration (Halpin and Woodhead 1998). In the unit pricing approach, the unit cost (dollars/unit) is applied to the quantity for a given line item to obtain an estimate of the work at hand. The dollars/unit is normally tabulated within a company or in standard references (e.g., R.S. Means) for a given line item as an average reflecting performance on a multitude of projects.

The resource enumeration method is more detailed. The estimator has to assume a given resource group (crew, equipment, etc.) for a given line item, calculate cost per hour for the assumed resource group, estimate its average production, rate and then modify it to reflect job efficiency. For labor intensive activities such as industrial construction, it is common to utilize a production rate, which is specified in man-hours/unit.

Such rates are generally tabulated as average values reflecting average conditions for a given project. An estimator generally starts with an average production rate and modifies it to reflect the conditions expected to be encountered on a specific project being estimated. For example, if the weather is expected to be unfavorable, or the available labor skill is low, the estimator will increase the number of man-hours/unit required to complete a particular activity.

The model described in this paper is mainly concerned with developing a consistent method that would allow the estimator to adjust the average productivity value to reflect specific project conditions in an accurate manner. This process, in practice, is currently highly subjective and presents challenges of consistency from one estimator to another and from one project to another. The intended domain of construction work targeted in this paper is industrial construction, which involves the construction of piping systems, typically for oil, gas, and petrochemical plants.

The model discussed in this paper is a set of artificial neural networks utilizing a two-stage process for predicting an efficiency multiplier (simply referred to as a ''multiplier'') that the estimator can use to adjust the average productivity thus reflecting specific job conditions that are anticipated. The model is a preliminary one based on a limited number of data points. It has been successfully tested in an industrial setting and is currently being populated with more data to increase its stability and add confidence to its predictions.

Artificial neural networks have been successfully applied to a variety of problems in construction. Karshenas and Feng (1992) assessed earthmoving equipment productivity using a modular neural network. Wales and AbouRizk (1993) used neural networks to predict the effects of environmental site conditions on the labor production rate within a simulation model. Chao and Skibniewski (1993) discussed a case study in which a neural network was used to predict the productivity of an excavator. Creese and Li (1995) developed a neural network model capable of estimating the cost of timber bridges. Sonmez (1996) studied the ability of neural network models to predict the labor productivity rates of concrete construction activities. Portas and AbouRizk (1997) discussed a neural network model developed to predict formwork labor productivity rates. A brief overview of neural networks is provided in the section entitled Neural Network Implementation.

The paper adds to the state-of-art cited above through the following:

- It identifies factors that affect labor production rates for industrial activities for the purpose of defining input to neural networks. This was achieved through a literature review and an internal survey of field personnel of an industrial contractor.
- It discusses the development and implementation of a two-stage neural network approach for predicting an efficiency multiplier useful in adjusting production rates in a consistent manner. This two-stage approach enhances prediction capability compared to normal back-propagation networks. It has applications in a variety of other problems where data are not harmonious, hence rendering successful training of a neural network infeasible.
- The models were automated and implemented at a major industrial contractor and proved to be effective in providing better consistency and accuracy compared to current practices.

This paper is organized as follows. The efficiency multipliers currently used for preparing estimates for pipe installation are discussed first. This is followed by a discussion of the factors that are considered to affect labor production rates. The artificial neural network model is presented in the third section

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while the conclusions are presented in the fourth section. It should be noted that the writers implemented neural network models for four different activities, but to keep the paper concise the focus will be on one activity, namely, pipe installation. Furthermore, to maintain confidentiality of data for the involved company the multipliers have been scaled.

EFFICIENCY MULTIPLIERS CURRENTLY USED BY COMPANY

The existing multipliers' table currently utilized by the estimators at the subject company range from 0.05 to 0.26. These multipliers are used to convert a standard production rate into a rate that reflects the expected conditions on the project at hand.

Actual production rates were collected from a sample of 27 completed projects involving 39 pipe-installation activities. The multiplier that should have been used was calculated by dividing the actual production rate by the standard production rate. The correct multipliers (ones that would yield exact production rates) for the sample of projects are summarized in Fig. 1.

From the histogram, the actual multipliers on 19 past projects (49%) were out of the multiplier range that the estimators had historically used (0.05–0.26). Over 28% of the multipliers (11 projects) exceeded the existing high multiplier value of 0.26 and subsequently were underestimated. On the other end, 21% (eight projects) were overestimated. From this simple analysis of past projects it can be concluded that the efficiency multiplier is not being properly predicted for a given project. More accurate predictions are obviously desirable.

The accuracy associated with selecting a given multiplier is a function of the following:

1. Properly considering all factors that impact the production rate for the type of work being estimated (e.g., design complexity, weather, labor skill, superintendent experience, etc.)
2. Properly projecting the condition that each factor will assumed when the job commences for the project at hand (e.g., expected good labor skill, excellent superintendent, etc.)
3. Properly quantifying the combined impact of all factors on the production rate, which results in the appropriate multiplier value

This paper addresses issues 1 and 3 above, which are discussed in the remaining sections. Issue 2 resides with the experience of the estimator and as such is not further examined in this work.

FACTORS AFFECTING PRODUCTION RATES IN INDUSTRIAL WORK

In identifying factors that impact production rates for a given activity the following process was followed:

- A literature review was first conducted to determine factors that need to be considered.
- A questionnaire was then prepared and was used to survey skilled workers, foremen, and superintendents to facilitate identification of further factors.
- Telephone and personal interviews with superintendents, project managers, and estimators was undertaken.

The results of this process are summarized in Tables 1–9, which categorizes 33 factors under nine groupings including general project characteristics, site, labor, equipment, overall project difficulty, general activity conditions, quantity, design, and activity difficulty.

General project characteristics cover factors that impact the entire project such as who was the designer, and who was the superintendent, and where was the project located. Site indicates how restricted the work area may be and the extent of prefabrication and modularization. Labor characteristics include crew size and whether the project is unionized or not. Equipment and material refer to the proportion of the cost of these items to that of labor. Difficulty of work is self-explanatory both at the project and activity levels. Finally, quantity of work and design details capture repetition and ease of work on the project.

DATA COLLECTION

Having identified the factors that could impact the labor production rate, actual data (regarding these factors and the corresponding production rate) are required to develop a model for predicting the proper multiplier for a given set of factors.

Collecting actual data involved two stages. The first stage involved organizing data, which already existed in project files or on the company's computer database. The second stage involved collecting information that was not available on record. Survey forms were designed to solicit the required input from field personnel. Data were collected through personal and phone interviews. This ensured that all input questions would be interpreted in a consistent manner and answered under similar assumptions and understanding. Fig. 2 shows a sample data collection form for activity information for pipe installation (the one used in this paper to demonstrate the approach).

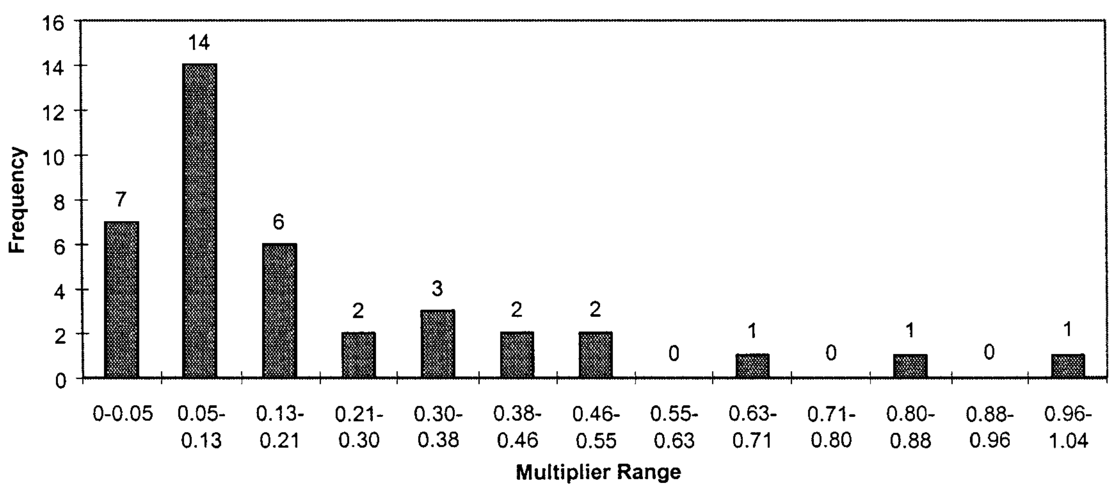

FIG. 1. Efficiency Multipliers for Pipe Installation (Handling) from Sample of Projects

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TABLE 1. Factors That Impact Labor Production Rates for Pipe Installation—General Project Characteristics

Number	Factor	Description
1	Location	Whether the project is located at an urban, rural, or camp job site may affect worker morale and the ability to obtain necessary or sufficient resources to properly undertake an activity. The skill level of the workers may also vary with the location.
2	State/province	This factor will distinguish the effect on productivity of differing working conditions, attitudes, practices, and regulations between states/provinces.
3	Administrative requirements	This factor compares the general expense man-hours used to the total direct man-hours spent on a project. This will indicate the level of planning and scheduling provided to the activities of the project.
4	Year of construction	This factor addresses differing work ethics, standards, and averages during different years of construction. This factor accounts for the differing time periods in which the historic projects took place.
5	Client	Client policies on quality, safety practices, working hours, and other conditions may influence the productivity of the workers.
6	Engineering firm	The engineering firms' abilities and practices may have a significant influence on productivity. For instance, an engineering firm that provides complete and well-organized drawings can make the construction simpler and more expeditious. Different firms will also have different response policies to queries during construction.
7	Superintendent	The ability of a superintendent to manage the workers on a worksite may have a significant influence on productivity. This factor was analyzed by examining the superintendents historical performances on past projects compared to the average historical performance of all general contractor projects.
8	Project manager	The ability of a project manager to manage a project may have an influence on productivity that is similar to the influence of the superintendent.

TABLE 2. Factors That Impact Labor Production Rates for Pipe Installation—Site Characteristics

Number	Factor	Description
9	Project definition	Industrial projects can be defined as one of eleven types of projects, including chemical plants, cogeneration projects, heavy oil plants, mining, oil and gas plants, petrochemical, pipeline and compressor stations, power production, pump stations, synthetic crude projects, and water treatment. Project definition can effect the productivity, as different projects may have different safety requirements, work hours, work conditions, or other conditions. This factor can also represent different difficulties present in each type.
10	Location of work scope	This factor accounts for conditions of the specific work location within an industrial site, which is either ''work confined to specific area'' or ''work scattered throughout plant site(s)''.
11	Project type	Whether the project is a plant upgrade where a shutdown is required, a plant upgrade where no shutdown is required, or new construction may have an influence on productivity. For example, in a shutdown situation working rates may be increased so that the product loss for the plant is minimized. Also, operating plants require additional permits and procedures; thus, projects require additional planning.
12	Prefab, modularization, and field work characteristics	This factor accounts for the effect on productivity of the location in which the piping system is constructed. Options include module prefabrication and site installation; shop prefabrication and site installation; and site prefabrication and site installation.

TABLE 3. Factors That Impact Labor Production Rates for Pipe Installation—Labor Characteristics

Number	Factor	Description
13	Average crew size	The influence of differing average crew sizes on the productivity of an activity is captured by this factor.
14	Peak crew size	Peak crew sizes occur during the high levels of construction on a project and may reflect a different influence on the productivity than the average crew size factor.
15	Unionized	Union rules and regulations and union worker's abilities and skills differ from those in a nonunion situation. This factor addresses these differences with respect to labor productivity.

TABLE 4. Factors That Impact Labor Production Rates for Pipe Installation—Equipment Characteristics

Number	Factor	Description
16	Equipment and material cost per direct man-hour	This factor is intended to identify what effect the ratio of equipment and material cost to the direct man-hours in a project has on productivity. For example, a lower than average ratio may indicate some equipment and material restrictions and, in turn, a decreased productivity.

TABLE 5. Factors That Impact Labor Production Rates for Pipe Installation—Difficulty Characteristics

Number	Factor	Description
17	Extra work	Extra work involves duties performed on a project that were beyond the original scope of the project. Extra work may indicate worse productivity achievements due to time spent on other activities and lower worker morale.
18	Change orders	Change orders require additional time for the adjustment of resources and man power so that the change can be met. Morale may also be affected by extensive numbers of change orders.
19	Drawing and specifications quality	This factor accounts for any difficulties encountered due to the provided drawings and specifications. Subjective judgment for this factor, in addition to the engineering firm factor, was deemed necessary to account for variability in the firm's output quality.

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TABLE 6. Factors That Impact Labor Production Rates for Pipe Installation—General Activity Characteristics

Number	Factor	Description
20	Learning	Extended duration may lead to better productivity due to the effects of the learning curve on an activity.
21	Location classification	This factor may determine the effect of the location of work within the site on productivity. Options include pipe installation in trench to 10 ft deep with battery limits of a process area installed before or during foundation work; pipe installed on pipe racks maximum 12 ft above grade; pipe installed in fabrication shop; pipe installed in a single-story building with maximum floor ceiling height of 20 ft; and pipe installed within the limits of a process area (i.e., vessels to 100 ft, pipe works to 20 ft maximum).

TABLE 7. Factors That Impact Labor Production Rates for Pipe Installation—Activity Quantities

Number	Factor	Description
22	Installation quantities	The actual handling quantities (ft).
23	Material type	Whether a material is a steel, plastic, or wrapped pipe may have a considerable influence on the installation productivity as weight and flexibility drastically differs between the identified materials.

TABLE 8. Factors That Impact Labor Production Rates for Pipe Installation—Activity Design

Number	Factor	Description
24	Method of installation	This factor will analyze the effect of differing percentages of machine and hand rigging on productivity.
25	Pipe supports	The quantity of pipe supports required for an activity may indicate the level of detail of the system being installed. Pipe supports, however, have only been tracked to a project level rather than activity level.
26	Boltups	Boltups, much like supports, may also indicate detail in an activity. These data are available to activity level, and therefore, this factor may be a better indicator of the effect of detail on the productivity of an activity in the neural network.
27	Valves	Valve quantities are the third item, which may indicate detail in an activity.
rr28	Screwed joints	The quantity of screwed joints quantities are the final item, which may indicate detail in an activity.

TABLE 9. Factors That Impact Labor Production Rates for Pipe Installation—Activity Difficulty

Number	Factor	Description
29	Season	Constraints or slow down in efficiency may result in pipe installation activities due to weather effects (e.g., cold weather, rain, high wind, etc.).
30	Crew ability	The ability or skill level of a crew may have a significant effect on productivity. This factor is only obtainable, however, in a subjective manner—the opinion of the project superintendent. The superintendent is asked to rate the ability of the crew, with 1 being low and 5 being high. Descriptive responses assigned to each number, however, may aid in eliminating a level of the subjective nature.
31	Working conditions	Such problems as congestion, site-access difficulties, or weather problems may have an influence on productivity. This factor is subjective and is therefore captured on a scale of 1–5, where 1 reflects many problems and a rank of 5 reflects no problems.
32	Inspection, safety, and quality requirements	The level of owner inspection, safety, and quality requirements on an activity may affect productivity. The superintendent ranks this factor; thus, it is subjective on a scale of 1–5, where 1 refers to extremely detailed requirements and 5 reflects highly tolerant requirements.
33	Overall degree of difficulty	This factor is also subjective in nature. Its intent is to capture any difficulties that are not captured through the previous factors.

A total of 27 projects were analyzed resulting in factors and associated labor production rates for 39 pipe-installation activities.

This data set was then statistically analyzed for significance, consistency, and integrity. The following section provides a summary of the analysis—the interested reader is referred to Knowles (1997) for further details.

ANALYSIS PROCEDURE

For the purpose of statistical analysis, the 33 factors are considered to be independent variables, while the multiplier is the dependent variable. The effect of various factors on the multiplier was assessed by using correlation and scatter plots and through building regression models. Table 10 shows the correlation between numeric factors and the multiplier (text-based factors are not included). Correlation confirms that the most significant factors are the ones related to activity difficulty and detail (boltups, valves, and screwed joints with correlation values of 0.627, 0.655, and 0.413, respectively). Closely following these factors are the ones related to project personnel (superintendent at 0.577 and project manager at 0.456) and then project owner and designer (0.356 and 0.301, respectively). On the other hand, ''learning'' and ''machine rigging'' had negative correlation to the multiplier as expected at −0.243 and −0.318 (i.e., they decrease the number of man-hours).

NEURAL NETWORK IMPLEMENTATION

A neural network is used to learn patterns and relationships in data (process referred to as training). Once trained, the neural network can be used to solve problems similar to the ones it was trained on (a process referred to as recall). Neural networks are generally composed of processing elements (PE) (represented graphically by circles) and connections (represented by arrows) as demonstrated in Fig. 3. Input factors (such as factors that are thought to affect labor production) are generally represented by the ''input layer,'' while the output of the network is represented by the output layer.

Neural networks can be used for classification or prediction. In classification networks, the network learns how to group

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Pipe Installation Report

Prepared By: ______________________ Report Date: ______________________

1. General Information

Project # : *Sample* Project Name: ______________________

Cost Code: *1* Classification: *1*

Cost Code Description: ______________________

2. Costs

Was fitup time included in the pipe handling cost code? Yes No N/A

Was hydrotesting coded separately? Yes No N/A

Were supports coded separately? Yes No N/A

Were valves coded separately? Yes No N/A

Was the assigned classification code adequate for this activity? Yes No N/A

3. Design

	Quantity	Quantity / Total Ft of Pipe
Total Pipe Supports		
Boltups		
Valves		
Screwed Joints		

3. Activity Difficulty

Method of Installation (Provide % of each): Machine Rigging ______ % Hand Rigging ______ %

What season was the activity completed in (assign % of activity time to each season)

Summer (above freezing): ______ % Winter (below freezing): ______ %

Rate the ability of the crew for this pipe handling activity 1 2 3 4 5
(1 - low, 5 - high)

Rate the site working conditions for the pipe handling activity 1 2 3 4 5
(1 - many problems with congestion, site access and/or weather, 5 - no problems)

Rate the owner inspection, safety and quality requirements 1 2 3 4 5
(1 - extremely detailed inspection, 5 - highly tolerant requirements)

Rate the overall degree of difficulty for the activity 1 2 3 4 5
(1 -high, 3 - average, 5 - low)

4. Productivity Rates

		Actual Project Stats			*Corporate Stats*		
Cost Code	Cost Code Description	Quantity	MH	Prod.	P% 10	Mode	P% 90
1							
1							
1							

Additional Notes

FIG. 2. Pipe Installation Questionnaire

the data into a number of classes based on the input provided to it. When new information is inputted, the network classifies it into the appropriate class. Prediction networks estimate an output for a given set of input. A comprehensive overview of neural networks can be found in Flood and Kartam (1994a,b).

The neural network structures utilized in this application represent an extension to the network approach described by Portas and AbouRizk (1998). The aforementioned network is a three-layer back-propagation structure with a fuzzy output layer. The output, as such, is presented in the form of a histogram reflecting the likelihood of the production rate rather than a single-point estimate. The user of such a network can then make a subjective judgment regarding the rate to be used or alternatively make use of the weighted average of the rates given by the histogram.

The approach described in this paper uses a similar network structure with one major difference. The production rate data set is divided into two classes based on whether the case reflects ''typical'' or ''nontypical'' production. By reference to Fig. 1, typical multipliers are the ones mostly encountered, which are represented by the lower three cells. Nontypical multipliers start with the third cell and on. The two classes overlap at the third cell providing a fuzzy region where productivity can be defined as either typical or nontypical. The breakdown point was arrived at by careful examination of the data set with the estimators and the chief engineer at the company. This resulted in 25 records being classed as typical and 17 records as nontypical (note that overlapping records were included in both sets).

This classification provided two separate, yet harmonious, data sets where a back-propagation neural network would be easier to train than when including the whole set. The only difficulty is then to be able to tell where the record set would lie given that the production rate would not be known before-

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TABLE 10. Correlation between Various Factors and Multiplier

Factor/subfactor	Correlation
Administrative requirements	−0.084
Owner index	0.356
Designer index	0.301
Superintendent index	0.577
Project manager index	0.456
Prefab classification A	0.099
Prefab classification B	−0.125
Prefab classification C	0.052
Equipment and material cost	−0.194
Extra work	0.044
Change orders	0.099
Hand rigging	0.318
Machine rigging	−0.318
Percent winter	−0.151
Percent summer	0.151
Log quantity <2	−0.116
Log quantity 2–16	−0.137
Log quantity >16	−0.133
Learning	−0.243
Supports	0.095
Boltups	0.627
Valves	0.655
Screwed joints	0.413
Multiplier	1.000

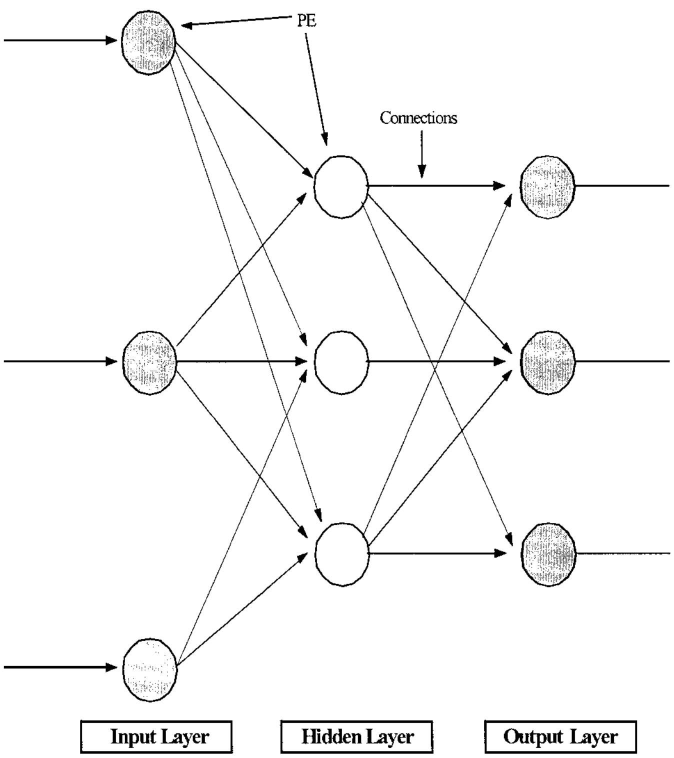

FIG. 3. Sample Three-Layer Back-Propagation Neural Network

hand—only the input factors are given. This problem can be solved by a Kohonen classification network, which can be trained to predict where the record would lie based on the input factors provided. The recall process can be summarized as follows:

- Estimator determines the values of the factors expected to be encountered on the project.
- The factors are fed to the Kohonen network, which predicts whether the production rate will be typical or nontypical.
- The appropriate back-propagation network (typical or nontypical) is then invoked to predict the value of the production rate.

This approach provided more accurate and more consistent predictions than the approach described in Portas and AbouRizk (1997). The process was automated so that the estimator enters the values for the input factors once and the appropriate results are generated. The process follows two stages, namely, classification and prediction.

Stage 1—Kohonen Learning Vector Quantization (LVQ) Classification Network

LVQ is a classification network first suggested by Kohonen (1995). The hidden layer, known as the Kohonen layer, does the learning and the classification. The input layer consists of one PE for each input parameter or factor. The output layer has one PE for each class. Each PE in the output layer has a cluster of PEs in the hidden layer associated with it and fully connected to it. In addition, each input PE is fully connected to every PE in the hidden layer.

The classification network utilized in this study is similar to the one shown in Fig. 4 where the input nodes are the factors given in Table 1. The values for the 39 records is first preprocessed and transformed into numeric input. For example, the year of construction is represented by equivalent binary input nodes, as there should be no preference between any two years, say 1995 and 1997. The mode of learning was ''supervised'' reflecting the fact that the input and the corresponding output were provided to the network for learning (as opposed to self-organizing networks).

The LVQ network consisted of 54 input nodes, 2 output nodes, and 5 PEs per classification output node within the hidden layer. The parameters were 0.06 learning rate, 0.06 repulsion rate, and 1.0 conscience factor. The network was trained with 85% of the data set (33 records) that were randomly picked, while 15% (6 records) were used for testing. To check for stability of the trained network, the training/testing process was repeated with different sets for a number of times. The accuracy of classification, on average, was 86% with the trained network, which is considered to be acceptable. Failed classifications were activities within 10% of actually being in the other class (overlapping zone). Therefore, classification is deemed a success and the addition of more training records is expected to increase the ability of the network to properly capture the ''borderline'' typical/nontypical activities.

Stage 2—Prediction Neural Network

Typical pipe installation activities are defined as the activities that achieved multipliers within the range that the estimators used historically. These activities essentially range from multipliers of 0.05–0.3 and compose the majority of the historic data. Given that this subset of the data is quite harmonious, it is expected that the feedforward back-propagation neural network will predict more accurately than if the two data sets were combined. The network is given in Fig. 5 and basically uses the same input as the classification network. It contains 35 hidden nodes and 14 output nodes. The number of factors used and their transformation dictate the input layer. The hidden layer is determined through the use of rules of thumb and a process of trial and error. The output layer is the one discussed in Portas and AbouRizk (1997). Essentially, the first node on the output layer predicts the production rate. The remaining 13 output nodes represent the cells of a histogram where the predictions are the likelihood of the multiplier being in a given cell as demonstrated in Fig. 6.

The training utilized 20 randomly selected records of the available 25 typical production rate records leaving 5 for testing. The process was repeated three times to confirm that the network is stable. The network predictive capability is demonstrated in Fig. 7.

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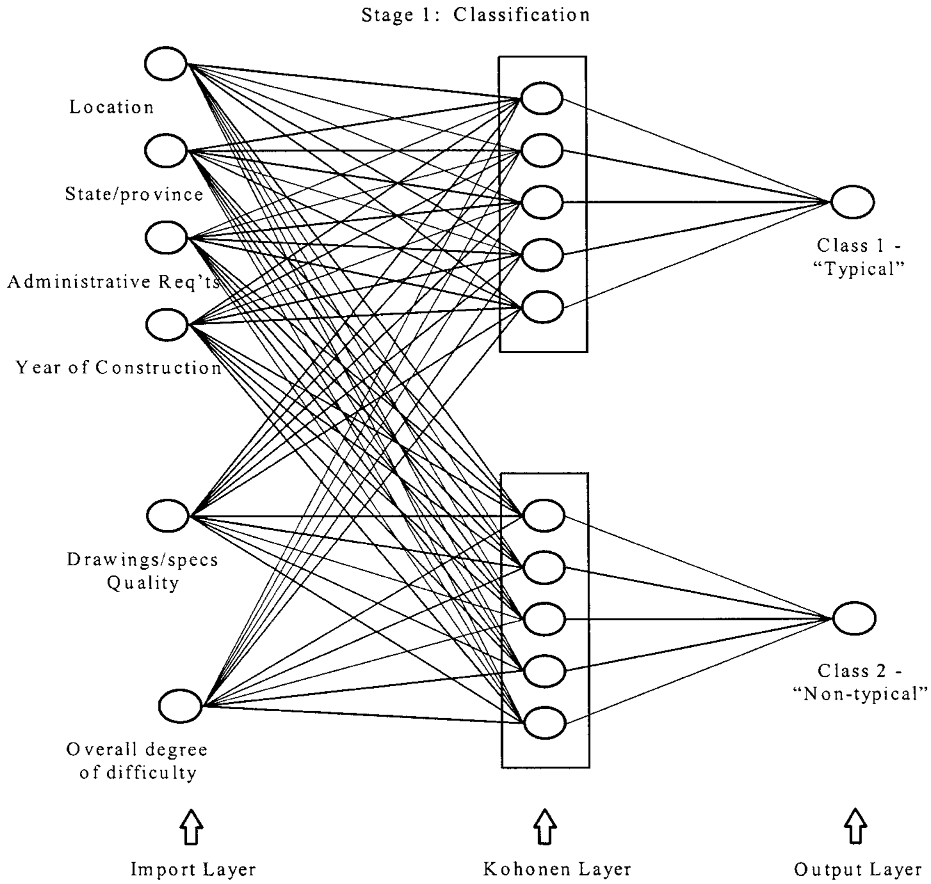

FIG. 4. Neural Network Structure

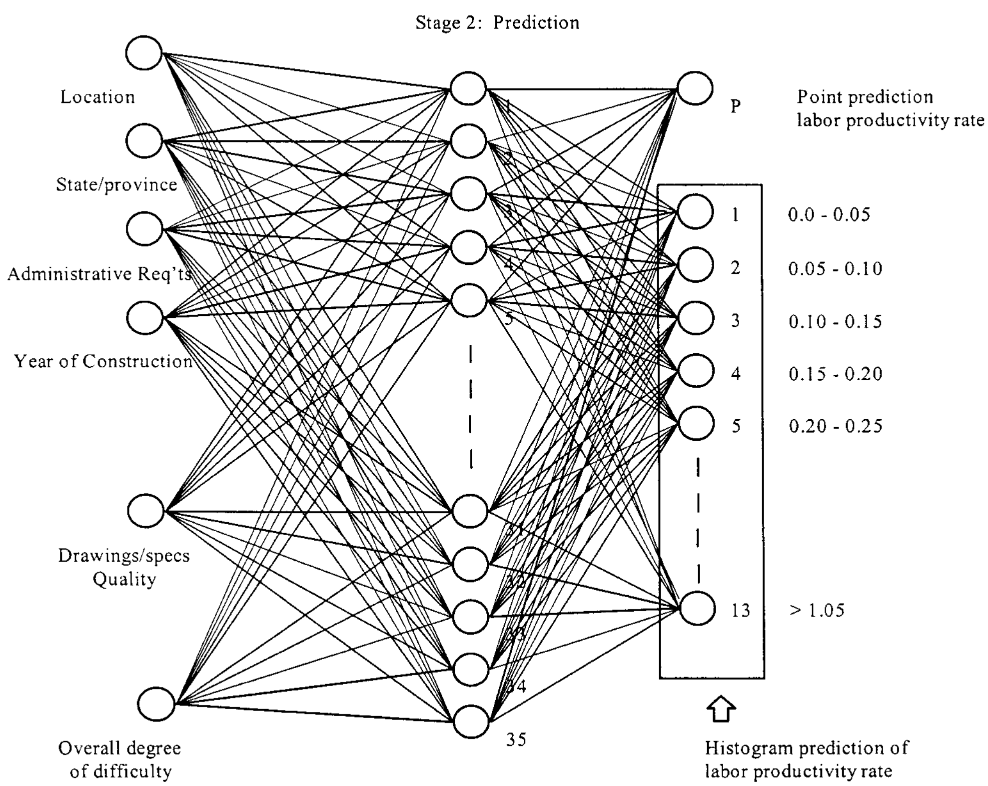

FIG. 5. Prediction Neural Network

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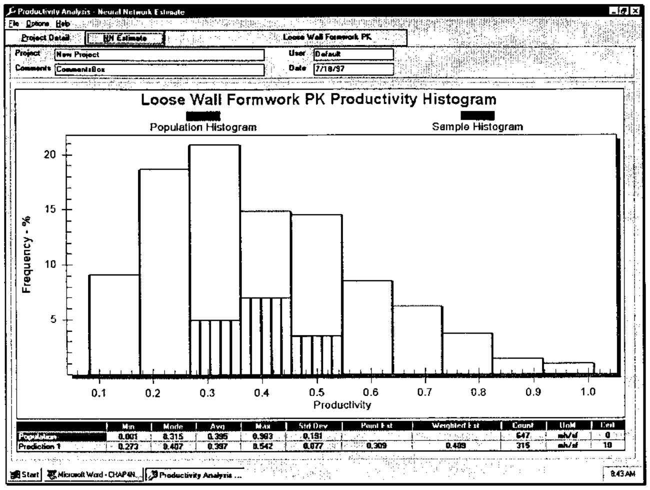

FIG. 6. Sample Fuzzy Output from Neural Network

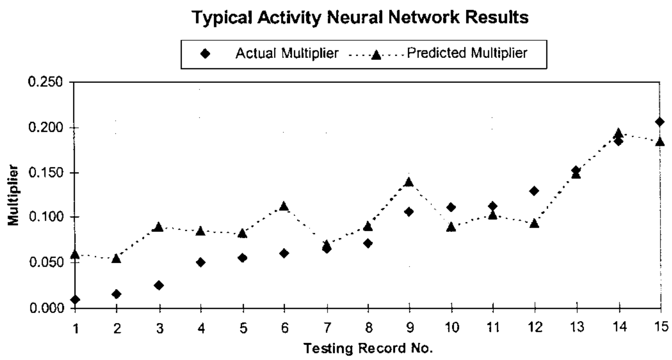

FIG. 7. Installation Testing Results Graph—Typical Activity Network

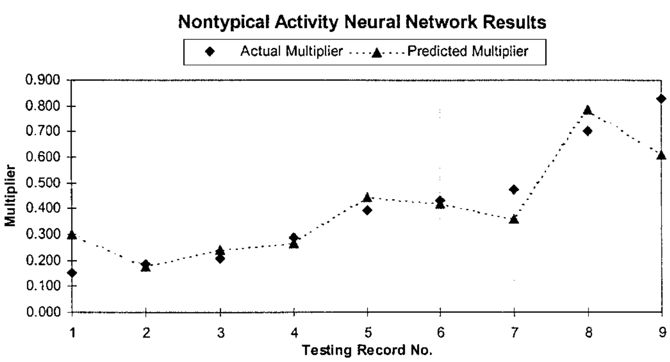

FIG. 8. Installation Testing Results Graph—Nontypical Activity Network

Nontypical pipe-installation activities are the activities that produce multipliers, which are not within the typical multiplier range. These activities are critical to identify and predict correctly because they have a significant negative effect on estimating labor costs.

The structure of the nontypical neural network is similar to the typical network given in Fig. 5.

The training utilized 14 randomly selected records of the available 17 typical production rate records leaving 3 for testing. The process was repeated three times to confirm that the network is stable. The network performance is demonstrated in Fig. 8.

Combined Results—Dual Neural Network System

The use of the two-stage neural network process resulted in a reduced error in pipe installation activity predictions compared to utilizing a simple back-propagation network, which was separately developed (Knowles 1997). The typical and nontypical neural networks predicted the multipliers to within 15% of the actual value on average a combined 84% of the time. This accuracy can also be expected to improve with increased data as both networks are trained with a minimal level of information.

A comparison of the performance of this approach to the classic single stage approach based on weighted average prediction of the multiplier (WAPM) calculated from the prediction cells in 13 output zones is summarized in Fig. 9.

Comparison between Actual Multipliers, Neural Network Predictions, and Values Currently Utilized by Estimators

To compare the effectiveness of the two-stage neural network model in predicting accurate multipliers, the following experiment was completed:

1. Of the 39 records that were collected 15% (5–6 records) were held for testing, while the rest were used for training in the two-stage process as previously described.
2. The predictions of the network were recorded for each iteration in the form shown in Fig. 6, which is the form estimators will normally use. The values were then transformed to an equivalent weighted average so that the use of subjective assessment in this experiment could be avoided (i.e., an estimator to give the predicted value from the histogram, shown in Fig. 6, was not relied upon; the predicted value was automatically calculated as a weighted average from the histogram).
3. Steps 1 and 2 were repeated three times with different training and testing sets to ensure that the network performance is stable. This process resulted in 21 test records, which were used to examine performance.

Fig. 10 summarizes the results recorded in the above experiment (the reader should note that the neural network plots of predicted values were the weighted average of the multiplier; the two-stage approach can also result in a fuzzy zone around each prediction, which is not shown here for clarity).

A simple review of the plots in Fig. 10 reveals that the two-stage approach tracks the actual multiplier values better than the current practice. In particular, records 13–21 (which represent overly difficult condition) were closely tracked by the neural network approach compared to the current practice (where the maximum multiplier value was applied).

In general, the predictions were accurate reflecting a reasonable level of confidence with the artificial neural network approach. In addition, the accuracy is expected to be further refined when more data becomes available as evident from the sensitivity study completed by Knowles (1997).

INDUSTRIAL USE OF ANN

The model described in this paper was based on a limited data set from 27 projects. Although its testing was successful at the involved company, efforts continue to date to increase the database and enhance the software. More recently, Hermann (1988) described a revised ANN model based on a larger data set from a wide variety of projects. The results were comparable to those in the original model indicating that the model was stable.

Furthermore, the model was fully automated to enable quicker collection of data and to allow its inclusion in future training of the network—a requirement for successful applications in industry. Finally, the ANN model proved to be primarily useful in reducing the subjectiveness of estimators from

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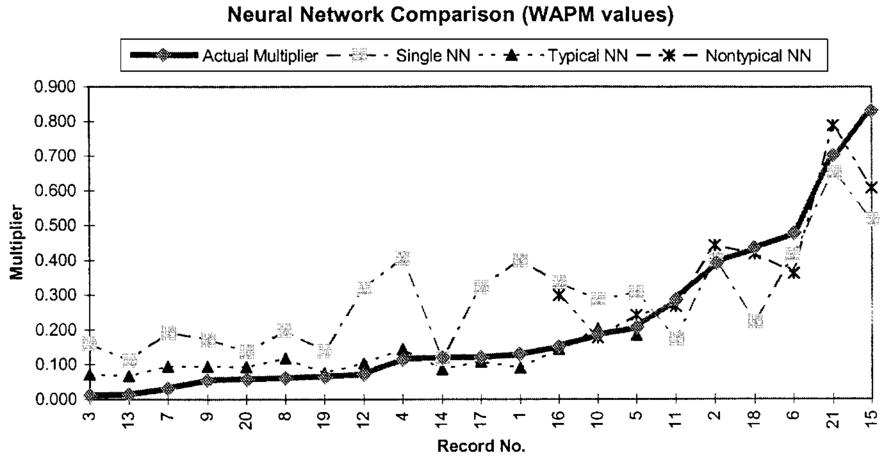

FIG. 9. Comparison of Two-Stage Approach to Single-Stage Classic Approach

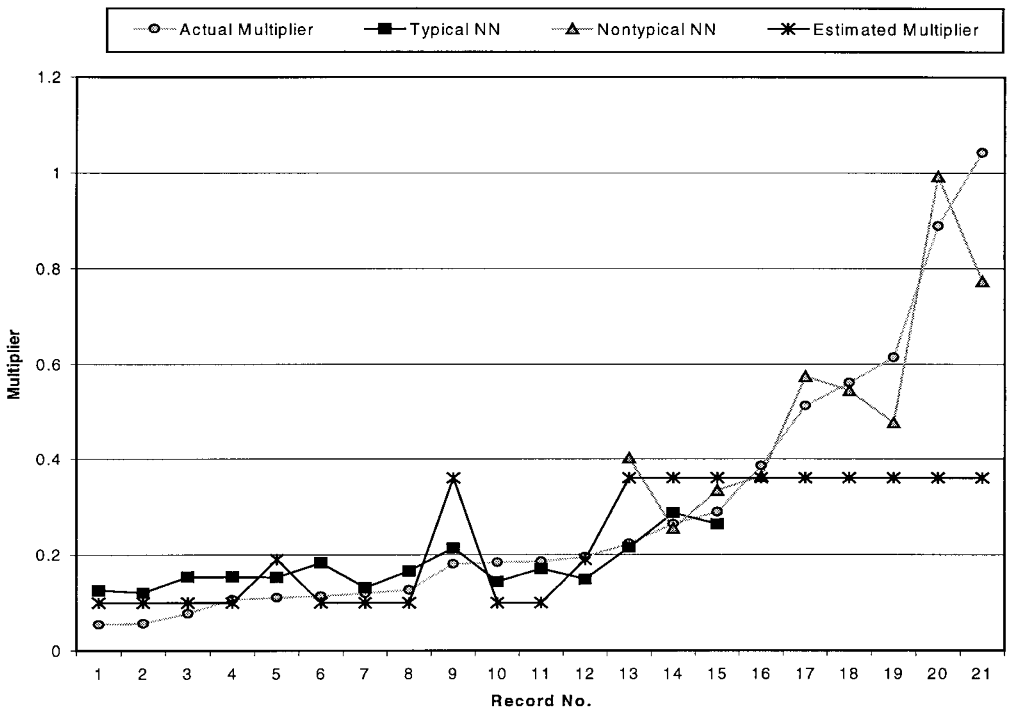

FIG. 10. Installation Neural Network versus Estimated Multiplier Comparison

one estimate to another, hence reducing the risk of incorrectly estimating new projects. This has a direct affect on the ability to correctly estimate new projects, which reduces the risk of not winning projects when the estimate is incorrectly high as well as winning projects when the estimates are incorrectly low. In the first case the company loses a bid, while in the second case it loses money on the project.

CONCLUSIONS

The most significant (and demanding) aspects of applying artificial neural networks in a practical application within an industrial setting are (1) defining input factors; and (2) collecting sufficient relevant data for training. The first aspect is best accomplished by the person most familiar with the environment for which the model is being developed. In this paper, the third writer, a senior engineer at the involved company, was able to lead this effort. The second aspect is best achieved through a carefully designed statistical experiment and by obtaining a real commitment from those that possess the information and the knowledge in how to retrieve it (either subjective or from archived company records).

Once the proper factors are identified and an appropriate number of records have been collected, the process of training the neural networks for classification or prediction, which is well documented in the literature, was straightforward. The requirements, however, were (1) not to totally remove the final decision about the multiplier value from the estimator; (2) to provide robust and stable predictions. The first requirement was achieved by training the two-stage neural network to predict its results on a fuzzy scale using the approach described in Portas and AbouRizk (1998) along with the normal one-point prediction of the multiplier. The estimator can then use what he/she is comfortable with. The second was achieved through the application of the two-stage process described in the paper. The two-stage process also improved the quality of predictions over the current practice as well as over the use of a single-stage back-propagation network. The networks predicted the multiplier to within 15% of the actual value on average a combined 84% of the time.

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