Measuring and Modeling Labor Productivity Using Historical Data

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Abstract: Labor productivity is a fundamental piece of information for estimating and scheduling a construction project. The current practice of labor productivity estimation relies primarily on either published productivity data or an individual's experience. There is a lack of a systematic approach to measuring and estimating labor productivity. Although historical project data hold important predictive productivity information, the lack of a consistent productivity measurement system and the low quality of historical data may prevent a meaningful analysis of labor productivity. In response to these problems, this paper presents an approach to measuring productivity, collecting historical data, and developing productivity models using historical data. This methodology is applied to model steel drafting and fabrication productivities. First, a consistent labor productivity measurement system was defined for steel drafting and shop fabrication activities. Second, a data acquisition system was developed to collect labor productivity data from past and current projects. Finally, the collected productivity data were used to develop labor productivity models using such techniques as artificial neural network and discrete-event simulation. These productivity models were developed and validated using actual data collected from a steel fabrication company.

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Introduction

By definition, productivity is the ratio of the quantity of input to the quantity of output. In construction, productivity is measured at different levels of detail for different purposes. For example, it may be measured to identify industry trends and to allow performance comparisons with other industry sectors (BFC 2006). Company-level or project-level productivity measurement provides internal and external benchmarks for comparison with company or project norms (e.g., Park et al. 2005; Ellis and Lee 2006). For detailed estimating and project scheduling, productivity is measured at an activity level, and because construction activities are normally labor intensive, productivity at the activity level is frequently referred to as labor productivity, which measures the input as labor hours and the output as installed quantities (Dozzi and AbouRizk 1993). Accordingly, productivity is measured by labor hours per unit of work, with other resource inputs, such as equipment and overhead costs, generally being correlated to labor hours. Measuring and predicting labor productivity for detailed estimating and scheduling purposes is the focus of this research. For simplicity, labor productivity is referred to as productivity thereafter.

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The current practice of estimating and scheduling relies on several sources to get productivity values, including an estimator's personal judgments, published productivity data, and historical project data. A survey conducted by Motwani et al. (1995) showed that more than 20% of contractors rely on estimators' "gut feelings" and opinions for the majority of their estimates. Obviously, the accuracy and reliability of this approach are influenced by personal prejudice and employee turnover. Standard productivity data are published by a number of companies and trade organizations, including the RS Means Company (RS Means 2007), which publishes annual construction cost and productivity data collected from contractors and trade organizations. However, published productivity data only represent average productivity rates of the industry and not the performance of any particular contractor. The most accurate and reliable estimate can usually be obtained from past project data, if they exist, such as project scope, progress information, and labor expenditures. These project data contain predictive productivity information that can be extracted for future project planning. The term "productivity modeling" refers to the approach of analyzing and estimating the impact of productivity-influencing factors on construction productivity using historical project data (Sonmez and Rowings 1998). Productivity data can be collected through a variety of sources, such as contract documents, progress reports, project databases, and time studies. By analyzing historical data, productivity models that evaluate the effect of these influencing factors on productivity can be constructed in the form of simple equations, nonlinear equations, or other advanced model forms. Once created, these models can then be used to predict productivity on future projects.

This research proposes an overall productivity modeling strategy of measuring productivity, collecting historical data, and developing productivity models. This is a multiyear research project conducted by a team consisting of university researchers and a steel fabrication company. This paper describes the challenges and the solutions in applying the proposed productivity modeling strategy in steel fabrication projects. A steel fabrication project consists of two major processes: steel drafting and shop fabrication. Steel drafting is one of the engineering functions at the detail design stage, in which draftspersons produce shop drawings for fabrication and erection in compliance with structural design, specification, and fabricator standards. Shop fabrication refers to the production of steel pieces through a series of operations, which normally include detailing, fitting, welding, and painting. Steel fabrication projects are labor intensive and include a wide range of labor disciplines, such as draftspersons, fitters, welders, and painters. As with other construction activities, estimating the productivity of steel drafting and fabrication is very challenging, and the current practice thus relies heavily on personal judgment.

The paper is organized as follows. The following section provides a literature review and discusses challenges in productivity modeling. The research methodology and objectives are then presented. This is followed by a discussion of problems and solutions in measuring steel drafting and fabrication productivity, collecting historical data, and developing productivity models.

Literature Review

The literature review was conducted in three areas regarding current industry practice and recent research: productivity measurement, productivity model development, and historical data collection.

Productivity Measurement

Productivity measures labor input per unit of work output. Although the measurement of the labor input can be consistently measured in terms of labor hours, the measurement of work output is rather diversified due to unique outputs produced by different construction activities. The output is normally measured by installed quantity, such as volume of earth hauled, concrete poured, or length of pipe installed. For example, Park et al. (2005) developed a common set of construction productivity metrics for benchmarking purposes that comprises 56 measurement elements in seven categories designed to measure output in terms of area, length, volume, weight, or simply a count of installed items. However, for some activities, multiple units may be applied to measure outputs from different perspectives. For example, the output from shop fabrication may be measured by weight, length, or a number count of pieces produced. None of these units can truly measure the complexity of work outputs and accurately reflect the effort required to produce them. Therefore, estimators may apply different methods to measure and estimate productivity based on their personal preferences.

Because steel drafting is within the scope of this research, a literature review was also conducted to arrive at an understanding of the current practice of engineering productivity measurement. A survey conducted by the Construction Industry Institute (CII) shows that the current practice followed by design firms is to determine engineering scope and output by relating them to the number of design documents for each design discipline (CII 2001; Diekmann and Thrush 1986). Engineering outputs are normally measured by the quantity of documents produced, such as drawings or specifications. However, Armentrout (1986) argued that due to the use of computerized design tools physical design documents do not truly reflect the total service provided by an engineering organization.

The literature review shows that there is no universally accepted productivity measurement standard for estimating purposes. For the same activity, productivity may be measured by different people in different ways, and the resulting productivity values are not directly comparable. In many cases, this inconsistency in measuring productivity makes productivity value difficult to understand and predict. Therefore, a productivity measurement standard must be established first and applied to present work processes before significant predictability of performance can be established (CII 2001).

Productivity Modeling Techniques

In addition to the inconsistent productivity measurement problem, another issue that contributes to the complexity of productivity estimating is the existence of numerous productivity-influencing factors, such as weather and labor skill. Productivity rates can fluctuate considerably due to the influence of these factors. Numerous studies have been conducted to examine the productivity-influencing factors of various construction activities, such as concrete construction (Sonmez and Rowings 1998), masonry construction (Sander and Thomas 1993), pile construction (Zayed and Halpin 2005), and bridge falsework (Tisher and Kuprenas 2003).

The relationship between influencing factors and the resulting productivity is very difficult to quantify. Published productivity data only represent industry average rates. Even a contractor-specific productivity standard reflects only the company's average past performance and serves only as a broad guideline for its estimators. Estimators' experience with the construction process and careful evaluation of productivity-influencing factors are crucial for producing an accurate estimate and schedule. Therefore, the current industry practice still relies heavily on individuals' judgments due to the uniqueness, complexity, and uncertainty involved in construction projects. However, this dependence upon personal judgment is limited by the level of knowledge and experience of a particular estimator and may not always produce consistent and reliable project plans. Therefore, a number of modeling techniques have been introduced to study the relationship between influencing factors and productivity for estimating purposes. These modeling techniques include statistical and regression models, expert systems, artificial intelligence, and simulation. For example, regression-based models were used to study earthmoving productivity (Smith 1999) and masonry productivity (Sander and Thomas 1993; Thomas and Sakarcan 1994). An example of using expert systems for productivity modeling is the system developed by Hendrickson et al. (1987) for masonry construction. Fayek and Oduba (2005) applied fuzzy expert systems to predict productivity of pipe rigging and welding.

Regression models are generally limited by the number of influencing factors that can be included and their capability of measuring the combined effect of the influencing factors. In expert systems, rules obtained from domain experts are affected by personal prejudices and attitudes due to the complex nature of productivity estimation. Moselhi et al. (1991) argued that artificial neural network (ANN) models are more suitable for modeling construction industry problems requiring analogy-based solutions than either traditional decision-analysis techniques or conventional expert systems. ANN has been used to model the relationship of influencing factors and construction productivity in various trades, including earthmoving equipment productivity (Karshenas and Feng 1992), concrete construction productivity (Sonmez and Rowings 1998), formwork production rates (Portas and AbouRizk 1997; AbouRizk et al. 2001), and pipe spool fabrication and installation productivity (Lu 2001). Another productivity modeling method, construction simulation, takes a different approach in that it explicitly models a construction process detail operations, influencing factors, resources, and their interactions. For example, Zayed and Halpin (2005) studied piling process productivity and cost assessment using simulation. Wales and AbouRizk (1996) proposed a process simulation model combined with a continuous-change weather process model to study the effects of weather on productivity. In this research here, ANN and simulation techniques are utilized to model steel drafting and fabrication productivity.

Historical Productivity Data Collection

To develop a productivity model, a large amount of comprehensive and accurate historical data is indispensable. This may mean that years of productivity data must be tracked and stored. Unfortunately, many contractors cannot take advantage of the productivity modeling approach due to the lack of accurate, consistent, and comprehensive data from past projects. First, many companies do not have a formal process for tracking and collecting actual project progress and expenditures, which means that historical data are simply not available for productivity analysis (Motwani et al. 1995). Second, data-collection procedures and methods may vary across different projects, which means that data are not available in a consistent and complete format that is suitable for meaningful analysis. Third, if data are collected in paper-based systems, the cost of data collection may be prohibitive due to the time-consuming nature of manual data retrieval (Azhar and Ahmed 2007). Finally, many companies use computerized cost-accounting systems or cost-control systems to produce productivity data. Unfortunately, for cost-control purposes, data are normally gathered at a summary level. For productivity measurement and estimating, data may also have to be tracked and analyzed at a more detailed activity or even operation level.

The lack of accurate, consistent, and comprehensive data from past projects has limited the application of many advanced productivity modeling techniques, such as ANN and simulation. Information systems and database technologies provide an efficient way to capture and manage project data for project control, but to make these information systems useful for productivity modeling, the data required for productivity modeling must be explicitly defined and considered during the information system development or upgrade process.

In summary, the literature review suggests the following issues that must be addressed: (1) how to define a reliable and consistent productivity measurement method; (2) how to efficiently collect historical data; and (3) selection and development of appropriate productivity models. The following section describes an overall methodology to address these issues.

Research Methodology

This research addresses the identified productivity issues through a systematic productivity modeling approach of measuring productivity, collecting historical data, and using historical data and advanced modeling techniques to model and predict productivity. The research aims at improving the current understanding of productivity measurement, data collection, and the selection and development of advanced models for productivity estimating. At the industrial level, the objective is to improve the collection and utilization of productivity data by standardizing its structure and enhancing its interpretation to improve the accuracy of project planning. Fig. 1 shows the research methodology, which contains three main stages: productivity measurement, data acquisition, and productivity model development.

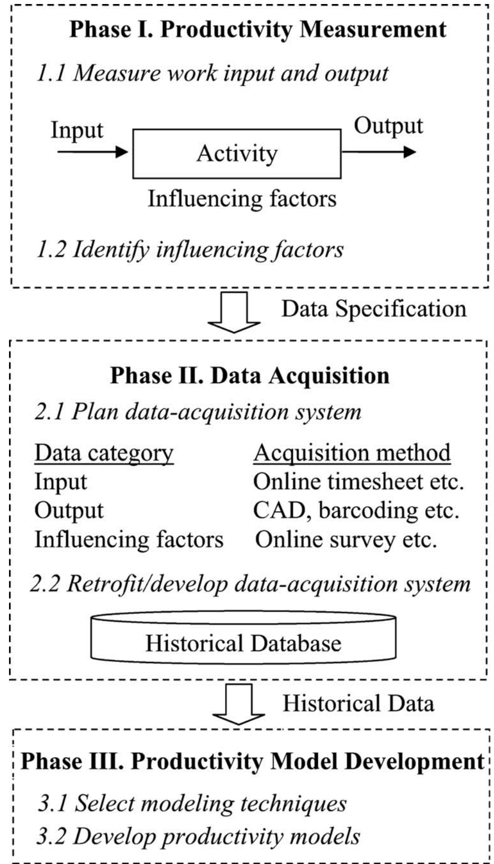


Fig. 1. Framework for productivity modeling using historical data

The method of measuring productivity is a fundamental decision that governs what data should be collected and what modeling techniques may be used. Although the input is measured in labor hours, several candidates for measuring work outputs may exist, so an appropriate output measure must be determined. Moreover, in this research, the productivity measurement concept is extended beyond the traditional view of input and output measurement to include the identification of productivity-influencing factors, because these influencing factors must be defined before historical data can be collected. These influencing factors are independent variables, and productivity is the dependent variable. Productivity factors can be identified by industry experts or through field observations. After the method of productivity measurement has been chosen and the productivity-influencing factors have been defined, a specification can be prepared to describe data requirements for productivity modeling, including data format and the level of detail required.

The second stage is to identify and implement data collection methods for the three categories of data required, including work input, output, and influencing factors. Characteristics of these data categories are different in many ways. Data may be subjective in nature, meaning that it can only be collected from project personnel, or they may be directly measurable in the field. The working environments of employees who can provide required data can also be very different. For example, office employees normally have access to personal computers for data reporting, but field employees often do not. These factors must be considered when defining data-collection methods for each data category. To ensure a consistent and cost-effective data-collection process, computerized data acquisition methods should be used as much as possible.

After historical data are accumulated, appropriate modeling techniques can be identified to study the relationships between influencing factors and the observed productivity. The selection of modeling techniques is primarily determined by the quantity and nature of influencing factors, the complexity of the mapping relationship, the capability of a particular modeling method, and the researcher's preferences. This research briefly describes ANN and simulation and their applications to productivity modeling.

Labor productivity is a fundamental piece of information for project planning, which is, in turn, a critical function to ensure a company's profitability, competitiveness, and continuous growth. Historical data collected from the proposed computerized data acquisition system can improve the accuracy of project planning. To achieve this benefit, the proposed approach suggests a company to invest in a computerized data acquisition system. Of course, the system development can become very costly. An investment for the sole purpose of productivity data collection and modeling is not likely to be successful for a construction company. To make the investment economically feasible, the system must be integrated into the overall information system framework of a company. A data-acquisition system may be implemented when a new information system is designed and implemented, or an existing information system may be retrofitted for the productivity-modeling purpose. In either case, a data-acquisition system must satisfy not only productivity modeling requirements but also information needs of business operations, such as time reporting, payroll, and project control. This dual-purpose investment strategy can make the investment profitable and improve top management buy-in.

In conjunction with a steel fabrication company, the proposed methodology is applied to steel fabrication projects. The following sections describe the challenges and the solutions related to modeling steel drafting and shop fabrication productivities.

Productivity Measurement

In the context of labor productivity, the input to an activity is measured by the quantity of direct labor hours charged to the activity, and labor hours are easy to understand and traceable. However, to measure the output, many candidates may exist, including those used historically as well as new ones that can be created. Criteria must be established for comparing and then selecting the most suitable measurement method. Statistical data analysis using historical data may also be conducted as part of the final selection process.

To determine the appropriate output measurement method, the following selection criteria are first established:

1. The output measurement should have high correlation with the labor hours and must be quantifiable.
2. The output measurement should be independent from productivity-influencing factors, such as site conditions and labor skills.
3. The output measurement should be easy to track and cost effective to implement.

Criteria 2 and 3 can be evaluated by subjective judgment. It is desirable to gather historical data and test Criterion 1, which is the correlation between the output measurement and labor hours, through statistical tests. Measuring steel drafting and fabrication productivities is described in this section.

Measuring Work Output

There is no standard measurement of outputs of steel drafting and various shop fabrication activities. Historically, the output of steel drafting is measured by weight, number count of steel pieces, drawings, or specifications. However, drafting has little to do with the actual weight of the steel. Further, because steel pieces and drawings vary so much in terms of complexity, a simple count of steel pieces or documents is misleading. The wide use of CAD drafting software also makes the quantity of drawings or paper size almost irrelevant. Similar issues can be observed in measuring outputs of various shop fabrication activities by weight or number count of steel pieces. As the complexity of each unit weight of steel or each steel piece may vary considerably, the amount of labor hours required to produce them will vary as well. In short, biased and inconsistent output measurement makes productivity value difficult to understand and estimate. For the same activity, productivity may be measured by different people in different ways, with the result that productivity values are not directly comparable. It was concluded that new output measurement units must be defined for steel drafting and steel fabrication activities.

In seeking a new measurement method, the research team proposed to identify a consistent way to measure drafting and fabrication outputs so that the overall production process could be controlled on the same basis. A piece-based approach was defined to measure the complexity of steel pieces on a piece-by-piece basis for both steel drafting and fabrication. During the steel drafting process, draftspersons detail each steel piece, such as a column or a bracing, and design the associated connections. As discussed previously, the complexity of drafting a steel piece varies significantly. Instead of directly measuring the output by the quantity of steel pieces, the degree of drafting complexity should be measured at the steel piece level. A "unitization" scheme was applied to quantify the complexity of a steel piece in terms of an abstract unit, named the "drafting unit." A simple column with no fittings is defined as a standard piece or one drafting unit. A degree-of-complexity factor or the number of drafting units can then be determined for a steel piece when it is compared with the standard piece. To make consistent measurements, a standard complexity factor matrix was compiled by experienced draftspersons and can be referred to in order to determine the number of drafting units of a steel piece. The detail implementation of this unitization scheme is available in Song and AbouRizk (2005). In reality, tracking the drafting productivity data of each single steel piece is not feasible, which prevents any direct measurement of productivity at the steel-piece level. The unitization scheme measures drafting output through a bottom-up approach and allows reporting of productivity at a higher work-package level, such as a division or a project level. Accordingly, drafting productivity is measured by hour per drafting unit at a work-package level.

During the steel fabrication process, steel pieces are cut, drilled, fitted, and welded one by one. Steel pieces are different in terms of weight, size, raw material, welds, and paint specifications, as well as the number of cuts, punches, holes, and fittings attached to them. Although productivity data in terms of work-hours per ton are available from historical data, estimators seldom use these numbers to estimate new jobs due to the uniqueness of steel pieces. In detailed estimating, estimators perform quantity takeoff and estimate the labor cost of every fabrication activity for every steel piece, with consideration for the complexity of steel pieces and the actual working environment. Theoretically, the above-mentioned unitization scheme can be applied to steel fabrication as well. However, unlike steel drafting, the productivity data of each steel piece can be collected through time studies, which means that the complexity of a steel piece and its processing time can be collected and used to explicitly measure productivity on a piece-by-piece basis. This approach is more accurate than the unitization method, which has to be based on a subjectively determined complexity factor matrix. Therefore, it was decided that productivities of individual shop fabrication activities should be measured directly as the processing time of a steel piece.

Verifying Output Measurement Using Historical Data

A quantitative way to evaluate the quality of output measurements against above-mentioned Criterion 1 is to perform a correlation analysis between the output measured by different units and the input. A good measurement of output should have a high correlation with the input, which is measured by labor hours. For steel drafting, a correlation analysis was conducted to compare the performance of drafting unit to other traditionally used units, including weight, quantity of drawings, and quantity of steel pieces. Historical data from a total of 59 steel drafting projects were collected from the collaborating company for the correlation analysis. These measurement units were compared and ranked by correlation coefficient, which indicates the strength of the relationship between a measurement method and labor hours. The correlation coefficients for drafting unit, drawing, weight, and number count of steel pieces are 0.88, 0.75, 0.67, and 0.53, respectively, showing that the drafting unit outperforms other commonly used units. A t test at the 95% level shows that the correlation is statistically significant. Thus, the drafting unit is selected to measure steel drafting output.

Measuring productivities of individual shop fabrication activities on a piece-by-piece basis is obviously more accurate than measuring solely by the weight of steel pieces, as the complexity and uniqueness of the steel pieces are not considered. The accuracy of the piece-by-piece method is statistically tested in the section of productivity modeling presented later.

Identifying-Productivity Influencing Factors

Productivity-influencing factors must also be identified and recorded for productivity modeling. Influencing factors that affect drafting productivity were collected through a literature review and interviews with draftspersons and estimators. A number of factors regarding project overall complexity, crew qualifications, and working conditions were considered relevant to drafting productivity. Several factors that were initially included were dropped because no variation was observed due to consistent practice, such as the CAD-based drafting method. Factors that describe the complexity of steel pieces, such as the percentage of bracings and the percentage of handrails, were not considered as influencing factors because they were already considered in the unitization method. Finally, 17 factors were identified, as shown in Table 1. The same procedure was applied to identify productivity-influencing factors for steel fabrication activities, such as steel fitting. The steel-fitting activity involves fit and tack-weld fittings to a steel piece temporarily for the final welding operation. Factors influencing fitting productivity include piece weight, piece length, number of cutouts and fittings, fitter skill level, and working shift.

Table 1. Productivity-Influencing Factors for Steel Drafting

Number	Factor	Description
1	Project type	Structural/plate work/both
2	Work scope	Supply only/supply and erect
3	Contract type	Lump sum/unit price
4	Piece cloning	Percentages of unique pieces over all pieces
5	Dynamic structure	Yes/no
6	Fireproofing	Yes/no
7	Special fall arrest provision	Yes/no
8	Overall complexity	1 very high, 3 average, 5 very low
9	Draftsperson qualification	1 very low, 3 average, 5 very high
10	Crew size	1–2, 3–5, 5+
11	Client	Index derived from historical data
12	Engineer firm	Index derived from historical data
13	Engineering standards	1 very low, 3 average, 5 very high
14	Administration	Percentages of administration hours over total hours
15	Overtime	Percentages of overtime hours over total hours
16	Subcontract	Percentages of subcontracts
17	Total work quantity	Quantity in drafting unit

During the productivity measurement stage, fundamental decisions are made regarding how productivity will be measured, the level of detail at which it would be measured, and what factors affect productivity. In this project, steel drafting productivity is measured by hour per drafting unit at a summary work-package level, and the productivity of an individual fabrication activity is directly measured by time consumed to process each steel piece. These decisions along with the influencing factors identified were documented in detail in a data specification, which describes the complete data requirements for designing a productivity data-acquisition system.

Data-Acquisition System

The data specification produced in the previous stage spells out all of the categories of data that must be collected. A data-acquisition system is a collection of data-collection policies, procedures, and techniques to capture productivity data from actual projects. The development of a data-acquisition system requires an examination of the nature of productivity data and careful evaluation and selection of data-collection techniques.

For the case study, required historical data include labor hours, activity output, and the values of productivity-influencing factors. These data categories can be collected at two different levels of detail, which are the work-package level and the individual-piece level. The first row and the first column of Table 2 show the data categories and the levels of detail, respectively. For steel drafting, labor hours of draftspersons and the values of productivity factors can only be reasonably collected at the project level in the col-

Table 2. Data Classification and Collection Methods

Level	Input	Output	Influencing factors
Work-package	Computerized timesheet	CAD-based quantity surveying	Online questionnaires
Piece	Time study (fabrication only)	CAD-based quantity surveying	Time study (fabrication only)

laborating company. For steel fabrication, labor hours and productivity factors can be collected at the individual-piece level. Meanwhile, work-package level data should also be captured for later productivity model validation purposes.

The selection of data-collection techniques is determined by the category of data and the level of detail required, as well as cost effectiveness, reliability, and user friendliness. These criteria ensure that a data-acquisition system is practical to use and that it will experience the lowest possible resistance from users. Data-collection techniques identified for each data category are shown in Table 2, including computerized timesheet systems, time study, CAD-based quantity surveying, and questionnaires.

Computerized timesheet systems were designed and implemented to track labor hours of both draftspersons and shop employees at the work-package level (Hajjar et al. 1999; Song 2004). These timesheet systems also satisfy the requirements for project control and payroll purposes. To study productivities of steel fabrication activities, productivity data at the individual-piece level must also be captured. Time study is still an indispensable way of collecting productivity data at this detail level, and so a time study was conducted periodically in a fabrication shop during a period of three months. Productivity data, along with influencing factors such as labor skill level and shift, were recorded during the time studies, and the collected data were used to analyze steel fitting productivity, which will be discussed later.

Measuring output is analogous to conducting a quantity survey. As discussed in the productivity measurement section, steel pieces have different degrees of complexity in terms of their physical attributes, which must be recorded for the productivity study. However, it is inefficient, if not impossible, to collect this information manually. CAD software tools are widely used in steel fabrication projects, and CAD models capture vast amounts of product data in an electronic format. Therefore, an automated software module was implemented to extract steel piece information from CAD models of historical projects (AceCAD 2003). For steel drafting, the extracted steel piece data and the predefined complexity-factor matrix were used to measure outputs from steel drafting projects in drafting units. For steel fabrication, these product data capture every steel piece and their physical attributes for further productivity analysis.

A questionnaire is a useful and organized strategy for collecting data that are undocumented or need subjective evaluation. To collect the values of influencing factors for steel drafting, a questionnaire was designed using the 17 factors identified previously, and data were collected for 59 past projects. A sample of the questionnaire is shown in Fig. 2. The chief draftsperson was also encouraged to provide such project information before project close-out or during the "lessons learned" session on future projects.

In addition to the above-mentioned data resources, the data-acquisition system also collected productivity-related information from the company's existing project management information system. The data-acquisition system was implemented within the framework of the collaborating company's information system, and it continuously collects data to support not only the daily business operations of the company, but also provides data required for productivity modeling. A number of hardware technologies, such as optical scanning, optical mark recognition, and bar coding, were used to streamline the data-collection process (Hajjar et al. 1999; Song 2004). This system enforces consistent data collection and centralizes comprehensive and accurate productivity data for productivity modeling. During a period of five years, over 800 Mbytes of historical project data were collected and stored in the company's central database system.

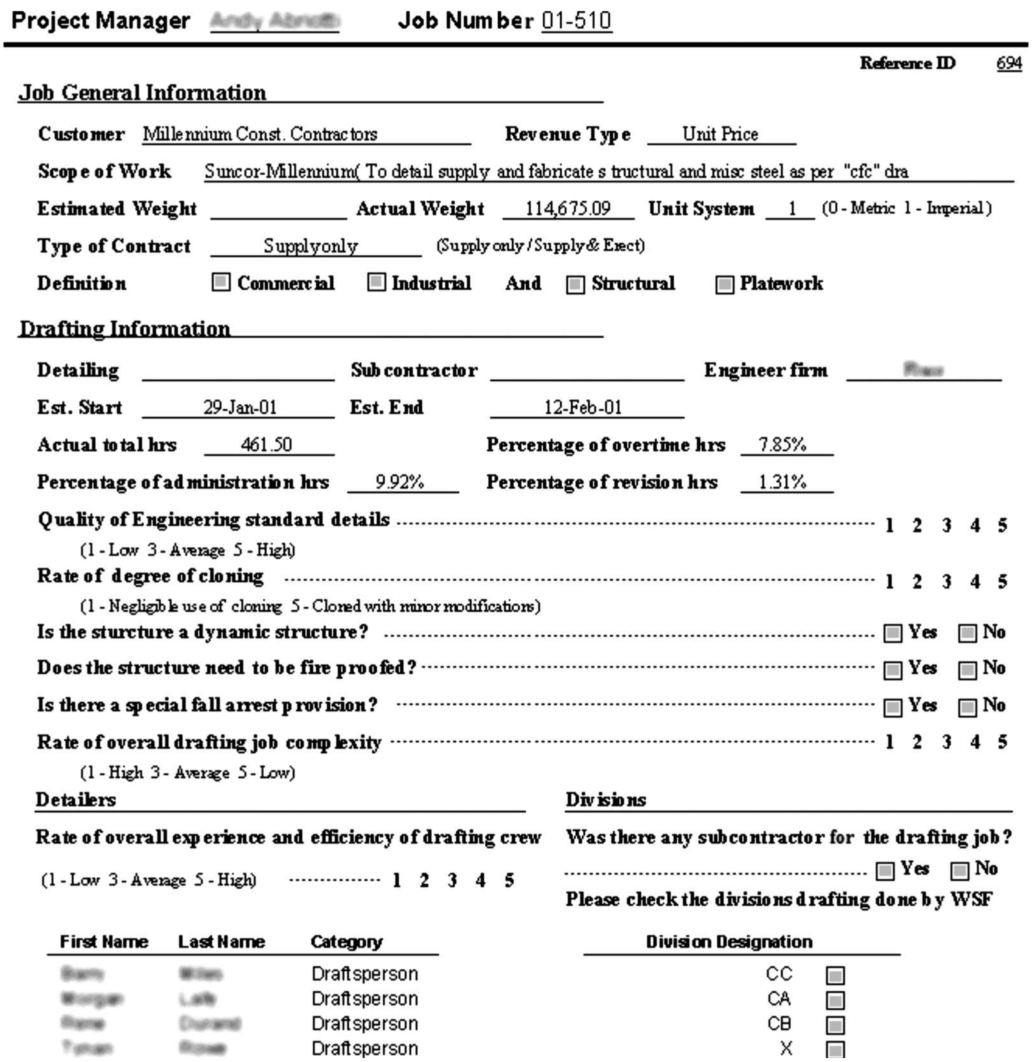
Productivity Modeling

By analyzing historical data, productivity models can be developed to quantify the mapping relationship between productivity factors and productivity rate for planning future projects. Two modeling techniques, ANN and simulation, were used to model steel drafting and steel fabrication productivities. This section describes model selection and implementation.

Model Selection

ANN mimics the pattern-finding capacity of human beings. The learning ability of ANN is achieved through a process of fitting a number of parameters using historical data. ANN is most suitable for modeling complex relationships that cannot be given in a precise and explicit manner, which is the case for steel drafting and shop fabrication activities, such as steel fitting. The drafting activity involves multiple stages of development, review, and revision, and, similarly, the steel fitting activity includes complex operations that are different from piece to piece. Further, breaking down these activities to a detailed operational level is not practical. Also, as discussed in the productivity measurement section, drafting productivity is affected by 17 factors and steel fitting has 6 influencing factors. As discussed in the literature review, ANN has been used by many researchers for modeling productivity of similar situations. The capability and accuracy of ANN in modeling steel drafting and fitting productivities is presented later in this section.

Modeling productivity at an activity level provides a local view of a particular activity's productivity. However, the overall shop fabrication process consists of a number of such activities, which work together as an integrated production system. The system productivity of a steel fabrication shop is not only determined by the productivity of individual activities but also influenced by system-level influencing factors, which include activity precedence relationships, queuing, resource interactions, equipment breakdowns, reworks, and other interruptions. In fact, to develop an estimate, estimators evaluate these factors by forming a production process model in their minds. To formalize this informal modeling process, a coherent and systematic method for productivity measurement and analysis at the system level is required. Discrete-event simulation involves the modeling of a system as it evolves over time using a representation in which the state variables change instantaneously at separate points in time (Law and Kelton 2000). Discrete-event simulation, referred



Project Manager [illegible] **Job Number** 01-510

Reference ID 694

Job General Information

Customer Millennium Const. Contractors **Revenue Type** Unit Price

Scope of Work Suncor-Millennium(To detail supply and fabricate s tructural and misc steel as per "cfc" dra

Estimated Weight ____ **Actual Weight** 114,675.09 **Unit System** 1 (0 - Metric 1 - Imperial)

Type of Contract Supplyonly (Supply only / Supply & Erect)

Definition ☐ **Commercial** ☐ **Industrial** **And** ☐ **Structural** ☐ **Platework**

Drafting Information

Detailing ____ **Subcontractor** ____ **Engineer firm** [illegible]

Est. Start 29-Jan-01 **Est. End** 12-Feb-01

Actual total hrs 461.50 **Percentage of overtime hrs** 7.85%

Percentage of administration hrs 9.92% **Percentage of revision hrs** 1.31%

Quality of Engineering standard details 1 2 3 4 5
(1 - Low 3 - Average 5 - High)

Rate of degree of cloning 1 2 3 4 5
(1 - Negligible use of cloning 5 - Cloned with minor modifications)

Is the sturcture a dynamic structure? .... ☐ Yes ☐ No

Does the structure need to be fire proofed? .... ☐ Yes ☐ No

Is there a special fall arrest provision? .... ☐ Yes ☐ No

Rate of overall drafting job complexity 1 2 3 4 5
(1 - High 3 - Average 5 - Low)

Detailers

Rate of overall experience and efficiency of drafting crew

(1 - Low 3 - Average 5 - High) 1 2 3 4 5

Divisions

Was there any subcontractor for the drafting job?

.... ☐ Yes ☐ No

Please check the divisions drafting done by WSF

First Name	Last Name	Category
[illegible]	[illegible]	Draftsperson
[illegible]	[illegible]	Draftsperson
[illegible]	[illegible]	Draftsperson
[illegible]	[illegible]	Draftsperson

Division Designation	
CC	☐
CA	☐
CB	☐
X	☐

Fig. 2. Sample questionnaire for steel drafting projects

to as "simulation" hereinafter, has been used to model many complex production systems in manufacturing and construction industries. Simulation models can accurately represent real-world systems at almost any level of detail, and the above-mentioned system-level influencing factors and their impacts on productivity can be explicitly modeled by simulation. This research applied simulation techniques to model the productivity of a steel fabrication shop.

ANN Modeling

The ANN modeling process involves data preparation, model training, and validation. For the steel drafting productivity study, 17 factors are identified as described previously. Draftspersons' labor hour allocation to steel drafting at the project level was recorded in a computerized office timesheet system, which is a component of the above-mentioned data-acquisition system. The quantity of drafting project outputs was calculated using CAD models and the unitization method, and the values of the influencing factors for historical projects were collected from the company's project management information system and questionnaire. A total of 59 drafting projects were included for ANN modeling. During the stage of ANN training, various network structure and training algorithms were investigated, and a learning algorithm, probability inference neural network (PINN) (Lu 2001), was found to be accurate and reliable. The training of the PINN model utilized 51 randomly selected records of the 59 drafting projects. The other 8 records were kept for validation. The developed model predicted the productivity to within 20% of the actual value 75% of the time on average.

The same methodology was also applied to modeling the productivity of steel fabrication activities. A study of steel drafting productivity is briefly described here. A time study of fitting activity was conducted during a three-month period in which labor hours and the six influencing factors were recorded. As discussed previously, CAD models supplied all product-related factors, such as piece weight, length, and the number of fittings. A total of 131 steel pieces and their fitting time were collected. The developed ANN model is a backpropagation network, and the output of the network is the fitting time of a steel piece. Neuroshell 2 was used to train the network (Neuroshell 2000). In total, 111 data points were randomly selected, and 20 data points were reserved for testing. The average absolute error was 0.75 min, and the maximum absolute error was 38.9 min for the test data set. Considering the wide duration range, the trained network is considered accurate in predicting the fitting duration with a satisfactory margin of error.

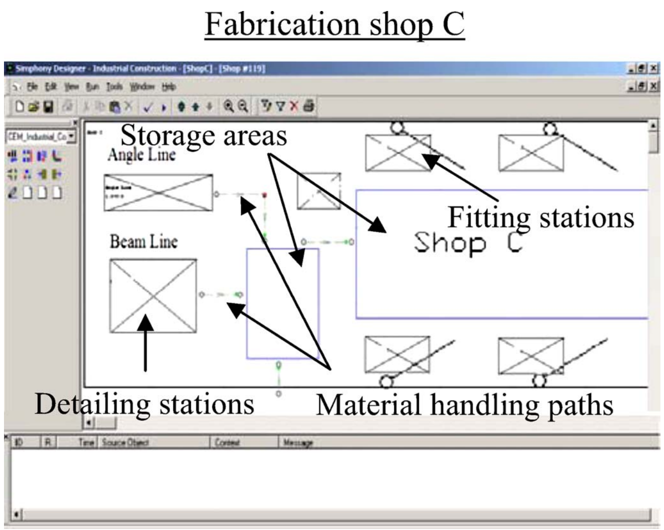


Fig. 3. Fabrication shop simulation model

Simulation Modeling of the Shop Fabrication Process

The objective of the simulation modeling is to simulate the entire shop fabrication process and the effect of influencing factors on productivity and project duration. A typical fabrication shop normally involves detailing, fitting, and welding. During the steel fabrication process, raw materials and steel pieces are handled by bridge cranes, jibs, and guided carts. Inspection and checking activities are also carried out at each stage of the fabrication process for quality control. System-level productivity-influencing factors considered in the simulation study include activity precedence relationships, queuing, material handling systems, equipment breakdowns, and reworks.

The developed steel fabrication simulation model consists of a product model and a process model. The product model stores all product definition data, including physical attributes of steel pieces and work breakdown structure information. The product model is populated by extracting product data directly from CAD models, as described in the data-acquisition system. The process model resembles a conventional resource-interaction simulation model that stores information regarding construction activities, resources, and their interaction. Data used to develop and validate the process model were collected from different sources. A shop employee timesheet system keeps track of labor expenditure data. Project information, historical rework rate, and equipment maintenance data are available from the existing project management information system.

A graphic simulation modeling tool was developed to simplify the model-development process. This modeling tool provides a number of basic elements, such as work station, storage space, and conveyor system (Song and AbouRizk 2006). These elements can be assembled quickly through a graphical user interface provided in Simphony, a discrete-event simulation software (Hajjar and AbouRizk 2002). Fig. 3 shows a screenshot of this shop model. ANN productivity models that predict individual activity processing time are embedded in the simulation model, and these ANN models are triggered when the simulation model requires estimating a steel piece's processing time. The estimated duration is then used to advance the simulation model.

The fabrication of 120 steel pieces was simulated using the model. The simulation experiment showed that the average total duration for shop fabrication was 1,778 min, with a standard deviation of 65 min and a 90% confidence interval of 1,564–1,884 min. The actual duration collected from the company's shop timesheet system is 1,875 min. This validated model can then be used to predict future project performance.

Conclusions

Historical data records a company's past performance and contains predictive information that is important for the company's future projects. This research proposes a systematic approach of measuring productivity, collecting historical data, and modeling productivity using historical data. This methodology is applied to measuring and modeling steel drafting and shop fabrication activities.

A productivity measurement method must be developed first to quantitatively measure labor input and work output and to identify factors that affect productivity. Decisions regarding how productivity is measured and what productivity-influencing factors should be considered determine the subsequent data-collection and modeling efforts. The case study of steel drafting productivity showed that consistent productivity measurement must be established before significant predictability of productivity can be achieved.

Based on the productivity measurement decision, a data-acquisition system must be implemented to keep track of labor input, work output, and productivity-influencing factors from past and current projects using appropriate data-collection techniques, which are determined by the characteristics of the data in terms of data source and the level of detail required. The decision must also consider a data-collection method's cost effectiveness, reliability, and user friendliness. Additionally, from an investment perspective, developing a data acquisition system for the sole purpose of productivity data collection and modeling is not likely to be profitable. To make the investment economically feasible, the system must be integrated into the overall information system framework of a company, and it should function both as a tracking system for daily operations of the business and as a historical data-acquisition system for productivity modeling.

The selection of productivity modeling techniques is primarily determined by the quantity and nature of influencing factors, the complexity of the mapping relationship, and the capability of a particular modeling method, as well as a researcher's preference. ANN and simulation were successfully applied in this research. ANN is found to be effective in modeling individual activities that have complex detail operations and a complex mapping relationship between productivity and influencing factors. Simulation combined with ANN was successfully applied to model the productivity of a production system that consists of a number of related activities. The proposed methodology and the industrial case study standardized the measurement of productivity in steel drafting and fabrication projects and improved the collection and utilization of productivity data by standardizing its structure and enhancing its interpretation and analysis.

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