Proceedings of the 2014 Winter Simulation Conference
A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, eds.

BIM-BASED DATA MINING APPROACH TO ESTIMATING JOB MAN-HOUR REQUIREMENTS IN STRUCTURAL STEEL FABRICATION

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ABSTRACT

In a steel fabrication shop, jobs from different clients and projects are generally processed simultaneously in order to streamline processes, improve resource utilization, and achieve cost-effectiveness in serving multiple concurrent steel-erection sites. Reliable quantity takeoff on each job and accurate estimate of shop fabrication man-hour requirements are crucial to plan and control fabrication operations and resource allocation on the shop floor. Building information modeling (BIM), is intended to integrate multifaceted characteristics of a building facility, but finds its application in structural steel fabrication largely limited to design and drafting. This research focuses on extending BIM's usage further to the planning and control phases in steel fabrication. Using data extracted from BIM-based models, a linear regression model is developed to provide the man-hour requirement estimate for a particular job. Actual data collected from a steel fabrication company was used to train and validate the model.

1 INTRODUCTION

Steel has long been the most important component to the construction sector for its strength, durability, flexibility, efficiency, sustainability, and versatility (SteelConstruction.info 2014). The production of steel pieces, which includes a variety of operations of detailing, fitting, welding, and surface processing, is a complex and critical process for a typical steel construction project. Most steel construction projects use off-site structural steel fabrication shops to support the erection sites in order to increase the productivity, gain better control over quality, and reduce the total cost of the projects (Eastman and Sacks 2008). A steel fabrication shop usually makes use of shift work and serves multiple steel erection sites at the same time to keep the business economical. Efficient planning is substantial to steel fabrication to ensure a streamlined and delay-free production process.

Figure 1 shows the structure of a typical construction project (Dozzi and AbouRizk 1993). Personnel, materials, equipment, and management are consumed by the system as resources to produce the construction units. As the foundation of further planning and scheduling, estimating plays a critical role to every construction project. Quantity takeoff is the most time-consuming yet extremely important task in estimating. The following project scheduling and control would benefit a great deal if quantity takeoff could be done accurately and in a timely manner. For example, it can be used to foresee and plan the construction activities during the pre-construction stage; in the process of construction, quantity takeoff can be used as a measurement of the project progress or for economic control of the project (Monteiro and Poças Martins 2013).

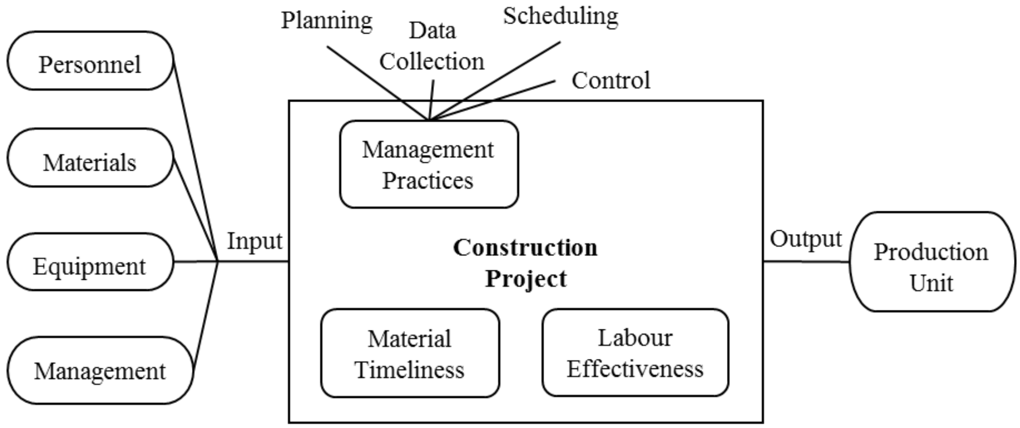

Figure 1: Framework for productivity improvement (Dozzi and AbouRizk 1993).

The measurement unit for workload for steel fabrication projects can be the number of steel pieces, weight of the final product, project duration, or monetary value. With the nature of steel fabrication being labor-intensive, man-hours are normally used as the major input for the steel fabrication processes (Dozzi and AbouRizk 1993). The other resources, such as labor, equipment, and overhead costs, are also closely correlated to man-hours. Therefore, it is most suitable to set the output of quantity takeoff as the man-hours needed to complete the project. In addition, the ratio of man-hours and the overall steel weight could be an excellent measure of production efficiency, i.e. productivity.

As defined by National Building Information Model Standard Project Committee (2014), BIM is "a shared knowledge resource for information about a facility forming a reliable basis for decisions during its life-cycle." The concept of BIM has been rapidly gaining popularity and acceptance since Autodesk released the BIM white paper (Autodesk 2003). Ideally, the vitality of a BIM-based model spans the entire life-cycle of a project, from earliest conception to completion, supporting processes like planning, design, cost control, construction management, etc. This relatively new technology has also been adopted by the steel fabrication industry, but only to find its use limited mostly to design and drafting (Sattineni and Bradford 2011). Most of the advantages that BIM offers, such as increased coordination of documents and effective information communication, are not exploited. BIM-based models are utilized solely as 3D visualization in most cases. The collaborating steel fabrication company for this research uses BIM software Tekla to build 3D models for structural visualization, and generate 2D drawings for the fabrication shop.

This paper presents an approach using regression analysis to extend BIM's usage further to the planning and control phase. The paper is organized as follows. The next section provides a literature review in construction estimating, application of regression analysis in construction, the current adoption of BIM in the steel industry, and background introduction. The research methodology is then presented, which is followed by model validation and evaluation.

2 BACKGROUND

To perform quantity takeoff, several methods are available in the construction industry. Traditional estimators do their takeoffs manually with printed drawings. They would use colorful markers to keep track of different materials and enter relevant information onto leger sheets or spreadsheets for calculation. Some estimators adopt simple annotation software to view electronic drawings, do color-coding, etc., but the process is still manual in essence (Vertigraph, Inc. 2004). Special estimating software is another approach, but its input still relies heavily on human interpretation. As stated by Saurabh Tiwari et al. (2009), "Model-based cost estimating is the process of integrating the object attributes from the 3D model of the designer with the cost information from database of the estimator." Adopting BIM for managing the design and construction process of projects has proven to be a shared understanding (Aranda-Mena et al. 2009). According to Monteiro and Poças Martins (2013), BIM-based quantity takeoff is "one of the potentially most important and profitable applications for BIM." Yet, it is still generally underdeveloped.

Artificial intelligence has long been adopted by researchers for modeling and solving problems in the construction industry. Modeling techniques such as artificial neural network (ANN), regression models, and decision trees have been introduced to study the relationships between all kinds of factors in construction processes using historical data. Song and AbouRizk (2008) used ANN to model the relationship of influencing factors and steel drafting and fabrication productivities. Jason B. Portas (1996) developed a neural network system to provide support in the labor productivity estimation for concrete formwork. ANN has also been used to model the relationship between influencing factors and construction productivity in trades like earthmoving equipment productivity (Karshenas and Feng 1992), concrete construction productivity (Sonmez and Rowings 1998), and pipe spool fabrication and installation productivity (Lu 2001). Hu and Mohamed (2012) explored artificial intelligence planning and dynamic programming to solve the automation problem in sequencing decision making in construction. Fayek and Oduba (2005) used fuzzy logic expert systems to predict productivity of pipe rigging and welding. Smith (1999) applied regression-based models to study earthmoving productivity. Lee et al. (2013) use regression analysis to develop a quantity prediction model for reinforced concrete and bricks in education facilities. Linear regression is also used to develop condition prediction models of oil and gas pipelines in order to provide decision support to practitioners in planning for pipeline maintenance (El-Abbasy et al. 2014).

A series of interviews with the estimators and project managers in the steel fabrication industry revealed that the current estimating practice followed by most steel fabricators is a manual process using spreadsheets and 2D drawings generated by computer aided design (CAD) software or exported from BIM-based models. Even with the availability of BIM, estimators use it as a visualization tool to help them with reading the 2D drawings. Estimators use their experience to evaluate the project complexity and estimate the workload. The factor of human interpretation in the process determines its error-proneness.

The collaborating company is a leader in the steel fabrication and construction services industries, offering services of procurement, engineering, 3D modeling, fabrication, coating, module assembly, erection, etc. They use Tekla software (Tekla 2014) to create 3D models from a customer's drawings, and produce erection and fabrication drawings. As shown in Figure 2, a job is divided into one or more divisions, which is of the proper size to manage and to be processed in different shops. Shops are equipped with different equipment and labor settings. For example, shop "A" is equipped with a 40-ton overhead crane, making it suitable to handle super assembly structures; shop "B" is set up to handle frames. A division is normally about 20 – 50 tons, consisting of multiple pieces. It is the basic unit for the estimators and project managers to do their jobs. The estimators or fabrication shop managers use their experience to evaluate the division complexity and come up with a labour productivity value measured by man-hours per tonne, which is to be multiplied by the overall weight of steel in order to get the man-hours budget needed to complete the work.

The effectiveness of this practice depends to a great extent on personal experience and knowledge, and may not always be consistent and reliable. The abundant information contained in BIM, such as predefined or user-defined material properties, is not exploited properly. Furthermore, job compositions of steel fabrication projects can vary greatly from one another. Even within the same job or division, the labour requirements per unit weight of different material types are generally different. For example, a piece demanding extensive welding obviously requires more man-hours than a super-assembly connected by bolts.

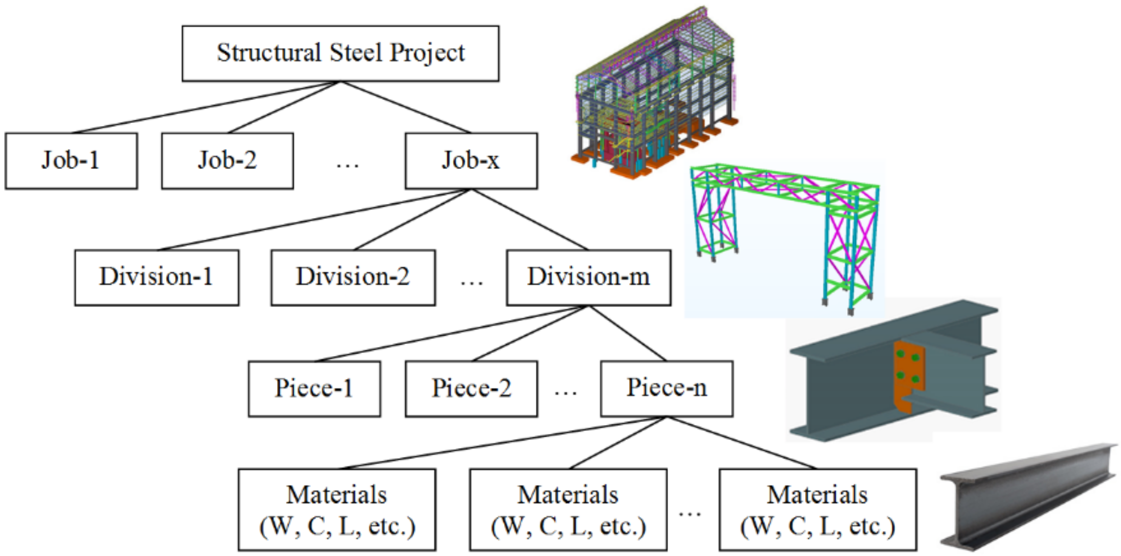

Figure 2: Hierarchy of a steel fabrication project.

This paper presents an approach to the prediction of fabrication man-hour requirements for structural steel projects by analyzing and learning from the historical schedules and cost information stored in the company's central database for the benefits of detailed estimating.

3 RESEARCH METHODOLOGY

BIM software has the functionality to create all kinds of reports of the information included in the models. Tekla Structures, used by the collaborating company, creates reports in the format of "*.xsr" files. The reports include lists of drawings, bolts, parts, etc. (Tekla 2014). Since the reports come directly from the model, the information is always accurate and reliable. This study makes use of the material parts report generated from Tekla. The essential attributes at the level of materials, as well as the summary level of divisions, are collected and analyzed for 298 jobs and 1605 divisions completed by the collaborating steel fabricator from 2009 to 2013. Only jobs that include supply work are considered because erection is a process almost completely separate from shop fabrication.

The first stage of this research is to design a meaningful data structure to sort out and organize the data at different levels, and to collect necessary information from the large database. After historical data are collected, a regression model is developed. The basic attributes of different material types are defined as independent input variables. The man-hours needed to fabricate a division are defined as the output variable. An open-source software, WEKA (The University of Waikato 2014), is chosen to complete the data mining task because of its wide collection of machine learning algorithms and various regression functions. The selection of contributing factors and the optimization of the variables through iterative experiments are all done by WEKA. At the third stage, the developed model is verified through an independent dataset and the prediction results are compared with the forecast made by personal judgment.

4 CASE STUDY

4.1 Data Preparation

A customized report template (*.rpt) is used in Tekla to create reports containing necessary information from the BIM models. A report contains too much information, so only part of the structure is shown in

Figure 3 as an example. The whole process of preparing the dataset for machine learning is summarized in Figure 4.

JOB#: 11-770
DATE: 20.10.2011 @13:54
BY:
FOR:
mm

PART NUMBER	REV	DESCRIPTION	QTY	WASTE FACTOR	UNIT WEIGHT {Kg's}	CAT	E-DRAWING NUMBER	CUSTOMER DRG NUMBER OR WORK TAG NUMBER	PROFILE
2A-1PSA	0	W-BEAM-B	6	0.00	113.81	5	E-2A-S30-530	RED-S30-530	W200X52
2A-2PSA	0	W-BEAM-B	4	0.00	93.02	5	E-2A-S30-531	RED-S30-531	W200X52
2A-3PSA	0	W-BEAM-B	1	0.00	133.00	5	E-2A-S30-531	RED-S30-531	W200X59
L56	0	W-BEAM-B	2	0.00	5.36	5	E-2A-S30-531	RED-S30-531	WT100X29.5
2A-4PSA	0	W-BEAM-B	1	0.00	133.00	5	E-2A-S30-531	RED-S30-531	W200X59
L56	0	W-BEAM-B	2	0.00	5.36	5	E-2A-S30-531	RED-S30-531	WT100X29.5
2A-5PSA	0	HS-BRACE-B	4	0.00	70.80	5	E-2A-S30-530	RED-S30-530	HSS127X127X6.4
2A-6PSA	0	HS-BRACE-B	2	0.00	68.50	5	E-2A-S30-531	RED-S30-531	HSS127X127X6.4
2A-7PSA	0	HS-BRACE-B	2	0.00	62.24	5	E-2A-S30-531	RED-S30-531	HSS127X127X6.4
2A-4000PSA	0	FR-ASS-B	1	0.00	329.95	5	E-2A-S30-530	RED-S30-530	W200X59
L1	0	FR-ASS-B	1	0.00	188.62	5	E-2A-S30-530	RED-S30-530	W200X59
L15	0	FR-ASS-B	1	0.00	329.95	5	E-2A-S30-530	RED-S30-530	W200X59
L22	0	FR-ASS-B	2	0.00	165.82	5	E-2A-S30-530	RED-S30-530	W200X52
L31	0	FR-ASS-B	1	0.00	88.40	5	E-2A-S30-530	RED-S30-530	HSS127X127X6.4

Figure 3: Tekla report example.

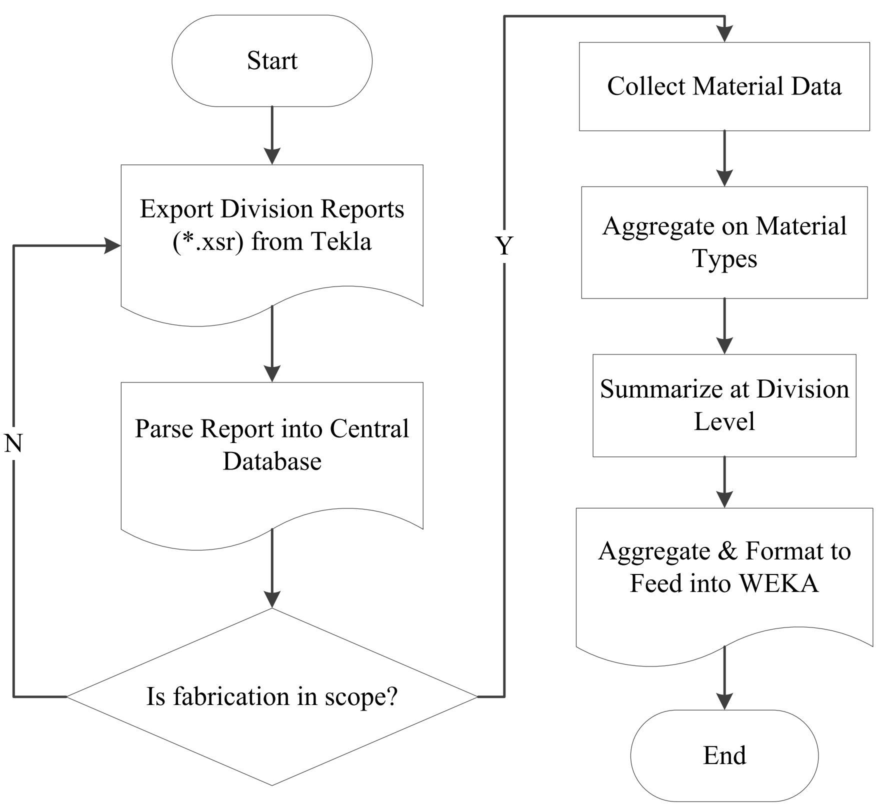

Figure 4: Data preparation framework.

In the central database, the production-related data is scattered over several tables. A general illustration of the object relations is illustrated in Figure 5. The physical steel materials are not directly associated with each division, but rather as parts of pieces and fabrication drawings. In order to study the productivity and schedule data at the division level, the detailed data of all the materials within the same division need to be collected and then aggregated to the division level based on material types. Divisions are assigned to different shops to be processed according to the characteristics of the division and the shops' capacities. Therefore the shop name is included as a nominal input of the model.

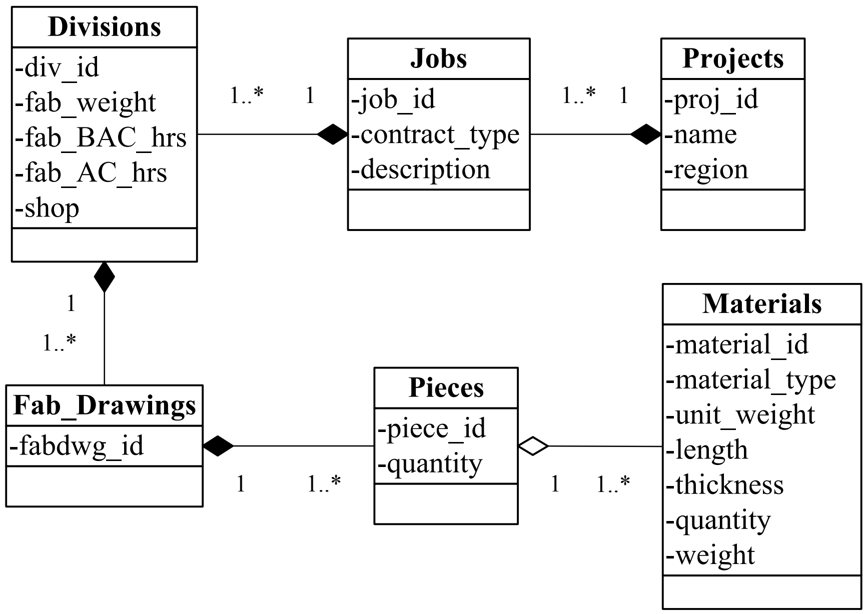

Figure 5: Fabrication information structure in database.

The unit weight per unit length, for example "kg/m," and quantity are the two most basic attributes of steel materials. For major materials such as beams, columns, and channels, the fabrication man-hours required are positively correlated with the material length and weight, but for the various kinds of bolts and nuts used in the shop, quantity would be a much more meaningful factor to be considered. The length of a bolt plays no role in determining the handling time of the piece it is attached to. Whether the bolt is long or short, it is the quantity that truly matters.

Table 1 lists part of the 45 material types examined in this study, according to the collaborating company's information library. Materials such as miscellaneous assemblies are excluded since their amounts and fabrication requirements are too small to make a difference.

Table 1: Part of material types and key attributes.

Material Type	Key Attribute
W – Wide Flange Beams	Length
L – Equal or Unequal Legs	Length
C – Channels	Length
HS – Hollow Steel Sections	Length
STD.PIPE – Standard Pipe	Length
M-BOLT – M Type Bolts	Quantity
H-NUT – Hex Nuts	Quantity

The basic attributes were collected at the level of each material type. Then the total quantity or length, and weight is summarized at the division level. The characteristics of one of the divisions to be fed into WEKA are shown in Table 2.

Table 2: Sample data of a division.

Characteristics	Division-1	Note
Division ID	18117	Input
Division Weight (kg)	28373	Input
Shop ("A", "B", "C", or "D")	"A"	Input
W Length (m)	13.89	Input
L Length (m)	9.27	Input
Plate Length (m)	78.06	Input
Flat Bar Length (m)	8.07	Input
Hex Type Bolts Quantity	381	Input
Fabrication Actual MHrs	875.57	Targeted Output
Fabrication Budget MHrs	692.30	Personal Judgment

4.2 Model Selection

It is generally believed that the more materials a job requires, the more man-hours it will cost. Accordingly, linear regression could be a suitable technique to use for quantitative man-hour prediction. Various types of models were investigated during the stage of model building and training. To get statistically meaningful results, 10 runs of 10-fold stratified cross-validation were performed on the training dataset (production data from 2009 to 2012) using different schemes. 10 iterations of 10-fold cross-validation means 100 calls of each scheme with the same dataset (Remco Bouckaert et al. 2014).

The Linear Regression implementation in WEKA uses the Akaike criterion (Burnham and Anderson 2002) for model selection. A statistical selection procedure is also incorporated in WEKA to determine the best combination of independent input variables. The selected factors and the regression parameters are given in Equation (1) in Section 4.3. Although ANN models are generally popular in the construction industry, they are more suitable for non-linear problems. RBF neural network was also tested in this study for comparison with the number of clusters set as the number of shops. Moreover, a Support Vector Machine with Sequential Minimal Optimization (SMO) algorithm (Platt 1998; Shevade et al. 2000) was tested. The Support Vector Regression (SVR) method defines an objective function on the training set with a constraint threshold, and the optimization objective is to find the best fit objective function while excluding the least outlying training data (Smola and Schölkopf 2004).

An evaluation summary of the different models is shown in Table 3. As expected, the RBF neural network model produces unsatisfactory results based on the current problem definition and dataset available. SMO regression's attempt to exclude outliers leads to a lower relative absolute error, and its performance can be considered statistically as good as linear regression. However, it is way more complex in nature than linear regression, probably leading to higher implementation cost and lower user acceptance. Therefore, linear regression is selected as the solution to the quantity take-off problem.

Table 3: Evaluation comparison of various models.

Evaluation Parameter	RBF	SMOreg	LinearRegression
Correlation coefficient	0.49	0.83	0.80
Mean absolute error	344.06	172.74	157.49
Root mean squared error	730.07	467.55	390.90
Relative absolute error	74.25%	37.28%	42.79%

4.3 Model Validation and Evaluation

The dataset from 2009 to 2012, which accounts for 248 jobs and 1343 divisions out of the total 298 jobs and 1605 divisions, is used to train the model. Data in 2013 is reserved for testing. To validate the model, 10-fold cross-validation was performed on the 2009-2012 dataset. Figure 6 shows the visualization of classifier errors of cross-validation results. The horizontal axis represents actual fabrication man-hours; the vertical axis represents the model-predicted man-hours. The closer the data points to a 45 degree line, the closer the forecast to the actual values. The method of tracking and recording actual hours on the floor is always improving. The historical data can have errors due to inaccurate records, for instance, working hours assigned to the wrong division number. The overall convergence in Figure 6 proves the validity of the trained model. The developed best-fit model is shown in Equation (1) below.

$$\begin{aligned}
divAct &= 0.015 \times divWt + 0.2036 \times W - 0.9271 \times WT \\
&+ 0.1708 \times C + 6.7115 \times MC - 0.2687 \times L + 0.7095 \times HS \\
&+ 0.8187 \times RD.HSS - 2.4378 \times STD.PIPE + 50.4317 \times XS.PIPE \\
&+ 11.5089 \times XXS.PIPE + 0.1645 \times PLT + 0.1334 \times HTB \\
&+ 2.1164 \times CHECK.PL - 0.29 \times FL.WASHER - 0.6684 \times BV.WASHER \\
&- 1.7614 \times NS.STUD + 10.776 \times CP.WELD + 1.5694 \times PP.WELD \\
&+ 0.4813 \times MBOLT.HEX + 340.4215 \times FabA + 15.054
\end{aligned} \tag{1}$$

Note: divAct = division actual MHrs; divWt = division weight; W = length of wide flange beams; WT = length of structural tees from W shapes; C = length of channels; MC = length of miscellaneous channels; L = length of equal or unequal legs; HS = length of square or rectangular hollow steel sections; RD.HSS = length of round hollow steel sections; STD.PIPE = length of standard pipes; XS.PIPE = length of extra strong pipes; XXS.PIPE = length of extra extra strong pipes; PLT = length of plates; CHECK.PL = length of checker plates; NS.STUD = length of Nelson S3L shear connectors and H4L headed concrete anchors; CP.WELD = length of complete penetration weld; PP.WELD = length of partial penetration weld; FL.WASHER = quantity of flat washers; BV.WASHER = quantity of beveled washers; MBOLT.HEX = quantity of hex head machine bolts; FabA = fabricated in shop "A".

Next, the 2013 data was used as a test set to evaluate the model. Figure 7 shows the correlation between the actual fabrication man-hours and the values predicted by the model. The better convergence of the data points in 2013 compared to the historical data can be due to the improved tracing and recording of actual hours. Limitations in the data are also suggested in the figure. For some divisions, the model tends to predict the work to be more than the actual man-hours recorded. One reason may be that when a worker is working on multiple divisions in a day, it is very likely that he fails to precisely track the number of hours he has spent in each division. Nevertheless, the figure clearly demonstrates that the trained model can be considered satisfactorily accurate in predicting the fabrication man-hours.

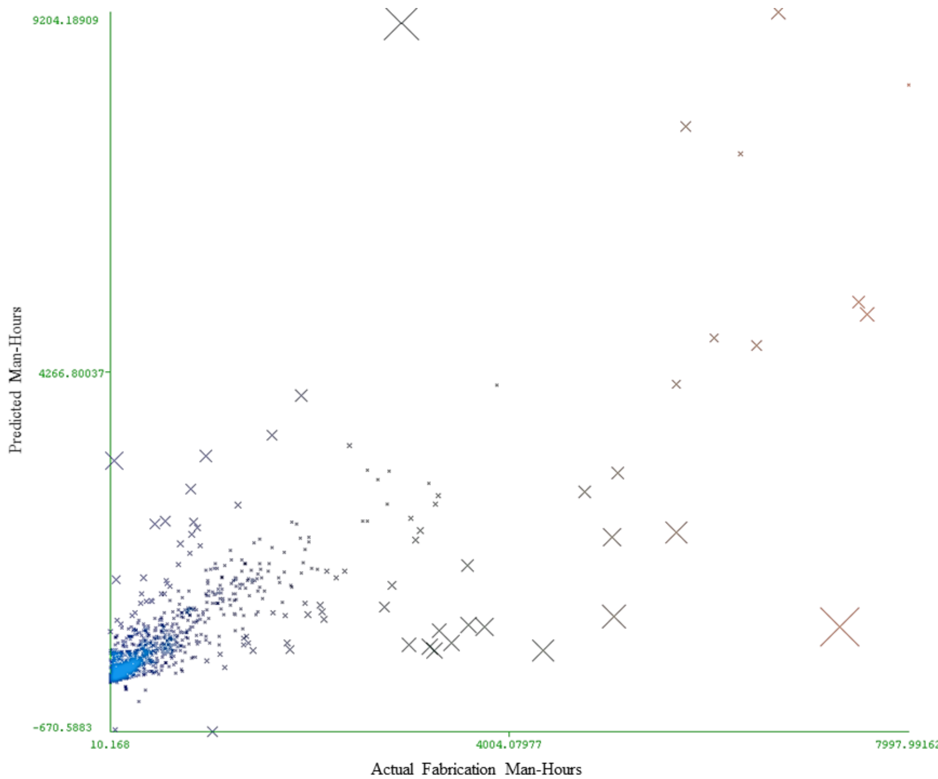

Figure 6: Ten-fold cross validation.

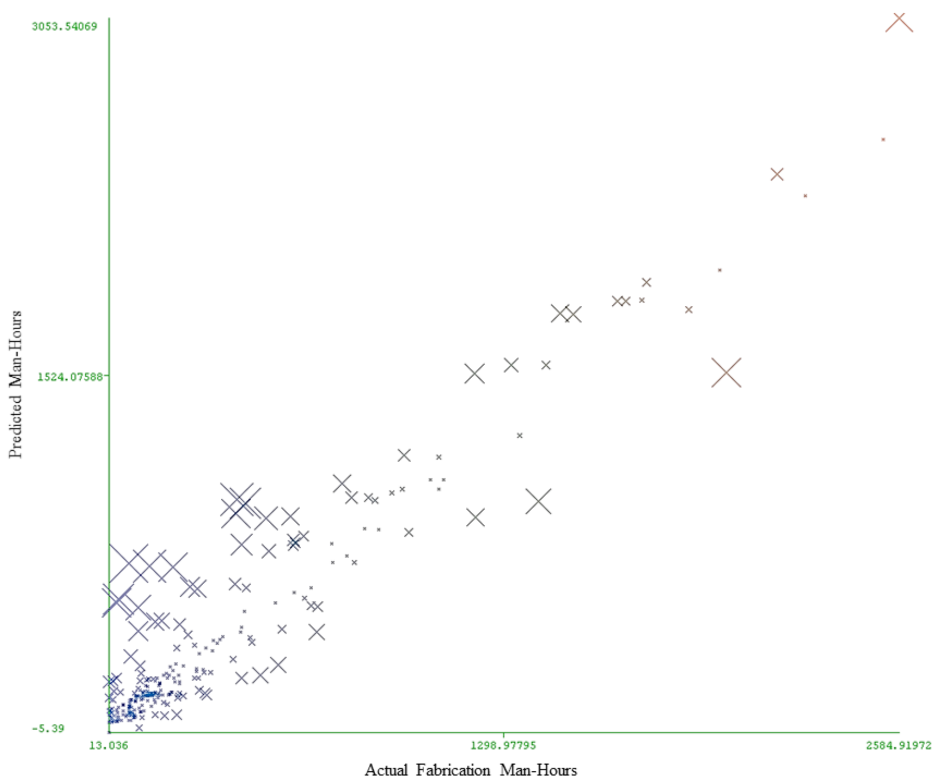

Figure 7: Evaluation on test set.

The shop budgeted man-hours are also compared with the actual fabrication man-hours. Shop budgets are the numbers produced by estimators following the current practice, which relies on the overall steel weight and a man-hour per ton factor from experience. The evaluation results can be found in Table 4.

Table 4: Evaluation summary of linear regression vs. experience.

Evaluation Parameter	Cross Validation	Linear Regression Prediction	Experience
Correlation coefficient	0.80	0.95	N/A
Mean absolute error	157.49	94.34	134.03
Root mean squared error	390.90	153.90	284.55
Relative absolute error	42.79%	25.01%	41.13%

The forecasted results are closer to the actual values than the judgment made by the professional judgment and experience. The increased accuracy in quantity takeoff will help optimize the company's resource allocation and reduce the risk of cost and schedule overrun. More importantly, the model can be useful as decision support or guidance for someone with little or no experience, especially when no detailed estimating handbook or manual, except a procedure guideline, is available. The estimating process can be accelerated and managers better assured.

5 CONCLUSIONS

Structural steel fabrication is an industry with characteristics that makes it different from traditional construction and manufacturing. The use of BIM is on the rise not only in general construction but also in structural steel fabrication. However, the functions and advantages of BIM-based models are limited to design and drafting in most cases. This research aims to develop an approach to extend BIM's usage further into estimating and planning. The performance information recorded in historical BIM data is important and useful for the company's future projects. This study develops a linear regression model to predict man-hour quantity for steel fabrication projects in the planning phase. The proposed methodology is implemented and validated, proving the models to be both feasible and recommended to support project estimating and planning.

The models were developed using the production data from the collaborating company, so that they were customized to the company's information management system (IMS). Another steel fabrication company may have different ways of tracking data and implementing IMS, but the methodology and framework of the study can still be used for the development of quantity take-off prediction models.

The results of this study show much promise for advanced BIM in steel fabrication planning and control. The combination of BIM with the current scheduling and fabrication process can be investigated in future studies. A target in the next phase of this research would be to develop an integrated system of estimating and scheduling, pushing the application of BIM further to the planning stage in steel fabrication shops. Related problems include how to determine the priority of various steel elements in scheduling, the complexity of the specific fabrication, and optimal allocation of the various resources on the shop floor.

ACKNOWLEDGMENTS

This project was funded by the Natural Sciences and Engineering Research Council of Canada under Collaborative Research and Development Grants (CRD). The authors wish to thank Darrell Mykitiuk and Jim Kanerva of Waiward Steel Fabricators Ltd. for their support.

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