

Intelligent Look-Ahead Scheduling for Structural Steel Fabrication Projects

Reza Azimi
Dept. of Civil & Environmental
Engineering
University of Alberta
Edmonton, Canada
razimi@ualberta.ca

SangHyun Lee
Dept. of Civil & Environmental
Engineering
University of Michigan
Ann Arbor, USA
shdpm@umich.edu

Simaan M. AbouRizk
Dept. of Civil & Environmental
Engineering
University of Alberta
Edmonton, Canada
abourizk@ualberta.ca

Abstract— Look-ahead Scheduling can be a difficult task, especially for non-repetitive, irregular work packages and activities such as occur in structural steel fabrication, where a variety of equipment, material and skilled work is required to manufacture unique steel pieces. Although punctual look-ahead scheduling based on the most recent system analysis and project data can significantly improve productivity and project control, this technique has not been extensively used in the construction industry. This paper presents an intelligent and integrated simulation-based framework in which real-time as-built data are captured and along with intelligently generated as-planned data are fed into the simulation model for look-ahead scheduling. A distributed simulation system based on the High Level Architecture is proposed to enhance the performance of the system. The ability of the proposed system to incorporate real-time actual data along with different scenarios that represent the dynamic work environment and external factors opens new doors to improve the accuracy of look-ahead scheduling in the construction industry. To exhibit the feasibility of the proposed framework, a prototype system is developed and deployed in a steel fabrication company.

Keywords: *Construction Simulation; High Level Architecture (HLA); project monitoring and control; real-time data capture, Artificial Neural Networks.*

I. INTRODUCTION

This paper amplifies the work originally presented in [1]. Currently, industrial steel structures are popular for constructing a variety of buildings, from heavy industrial buildings and petrochemical refineries to sheds, shelters, and roofs. Reduced construction times, efficiency, and cost-effectiveness can be considered as the major benefits of using industrial steel elements. Detailing, procurement, steel fabrication, shipment, and site erection are the five major phases in a typical industrial steel construction project [2]. Steel fabrication, one of the complex phases, refers to the production of steel pieces through a series of operations, including detailing, fitting, welding, and surface processing in a confined environment called a fabrication shop [3, 4]. Better control over quality, effective labor utilization, and reduction of waste are some advantages of manufacturing steel elements in a fabrication shop. Material handling and inspection activities occur frequently during the fabrication process. There are a large variety of steel pieces produced, in terms of both dimensions and processing requirements. Steel fabrication activities require an assortment of equipment,

material and labor disciplines in order to produce steel pieces.

The complexity and variety of products, and the large number of potential resources, activities, interactions, constraints and uncertainties, make the planning and control of ongoing and forthcoming steel fabrication projects a complicated task. Project planning involves several activities, including master scheduling and short-term or look-ahead scheduling, which are two key elements in successful delivery of the projects. Master scheduling refers to the overall view of the projects and general fabrication strategies. Such scheduling may be used for several reasons: forecasting demand, long-term coordination (e.g., regarding material requirements and staffing level) and rough budgeting. However, master scheduling suffers from a lack of information about actual durations and cannot be properly detailed far into the future. Conversely, a look-ahead schedule is a detailed plan for work packages to be completed in a relatively short time frame. Look-ahead scheduling helps project managers focus on the work packages that should be done at some time in the future and the corrective actions in the present that will lead to finishing those work packages on time, within budget and to a specified quality. These detailed schedules should be developed and updated in a timely manner based on the actual project performance data and the conditions in the construction environment, to precisely represent the tasks that have been done and the tasks that remain [5]. Such a detailed schedule is a solid foundation in terms of performance analysis and taking effective corrective actions.

This paper proposes a steel fabrication shop modeling approach for efficient look-ahead scheduling of steel fabrication projects in the Construction Synthetic Environment (COSYE) based on the High Level Architecture (HLA) infrastructure. In this approach, real-time, high-quality actual project data are captured and fed into a simulation model along with the uncertainties and the factors influencing the productivity of the fabrication shop. In this way, reliable updated look-ahead schedules are generated by the simulation model and “guesstimates” are rarely needed. Current practice and research carried out regarding look-ahead scheduling is discussed, and the conceptual framework of the integrated real-time simulation-based scheduling system is then described. The feasibility of the proposed framework is demonstrated by developing a prototype system that was used for a case study in a steel

fabrication shop. The advantages and limitations of the proposed system are also discussed in this paper.

II. BACKGROUND AND LITERATURE REVIEW

The basis of Look-ahead Scheduling (LAS) is similar to regular scheduling. Usually, activities or work packages are regular and predictable. When that is not the case, work packages need to be appropriately classified and work packages that are considered similar may differ in terms of process duration and required resources. Similar to regular scheduling, standard data should be generated using time studies or expert judgment. Once these standards are established, work packages can be scheduled, allowing foremen and project managers to forecast and control projects over comparatively short time intervals. LAS usually refers to a foreman's schedule, settled and tracked by foremen on a short-term basis. The foremen determine which work packages would be processed by their crew during the next few days, and the project managers monitor the accuracy of the schedule. This monitoring leads to identifying factors that affect the production rate. Once these factors are identified, the project managers can address the implicit causes and routinely enhance the accuracy of the LAS. LAS helps improve productivity by eliminating or reducing time spent that is not adding value to projects. It also helps ensure all the required resources and material are ready for ongoing projects at any time needed. Since LAS sets realistic and obtainable goals for a short time span, as a psychological effect, the workers tend to get the work done as soon as possible.

Smith [6] argues that LAS has been successfully implemented in different domains such as material handling, quality assurance, manufacturing, maintenance, engineering, and assembly operations. LAS has been largely used for mass production systems where immediate follow-up and corrective actions are a must in the case of deviations [7]. As an example, combined with pairwise comparison LAS was utilized for scheduling random operations in job-shops [8].

In spite of the fact that very little information on LAS is provided in the literature, effective LAS are crucial to the successful completion of construction projects [5]. Daneshgari and Moore [9] state that on average up to 70% of construction job schedules experience changes. They observed four projects over a four-month period, ranked the impact of the unscheduled activities on the lost productivity and concluded that implementation of LAS is a great tool to improve the productivity. Similarly, Hadavi and Krizek [10] concluded that short-term scheduling results in higher productivity compared to long-term scheduling. Studying decision support systems in manufacturing operations and determining the types of data required to plan and control effectively, Schmahl [11] concluded that LAS can be used to support continuous improvement efforts in production operations. Scheduling problems could be solved for either the next hour or the next few weeks by LAS [12]. Guidelines regarding developing work packages for effective utilization of LAS as well as the situations where LAS is more likely to succeed have been discussed by Ramirez-Valdivia et al. [7].

Finally, emphasizing the key role of LAS in enhancing production control, Ballard [13] proposed strategies for improving LAS.

In construction, many operations are repetitive and involve uncertainty and resource constraints. This motivated researchers to deploy discrete-event simulation for LAS problems [14]. Simulation is a mathematical-logical model representing a real-world evolving system. Users can use the simulation model to analyze and forecast the performance of a system considering different scenarios. Actual data captured from ongoing projects along with the uncertainties of the construction environment can be fed into the simulation model to "tune it up" for generating better results [15, 16]. A proper updating process for simulation input modeling based on high quality data is necessary to achieve simulation accuracy. The emergence of new technologies has enhanced data acquisition systems by providing automated high-quality real-time data. For example, Radio Frequency Identification (RFID) has been used to track real-time locations of steel pieces in a steel fabrication shop [2] and monitor steel works in high-rise buildings [17]. The same data acquisition system based on RFID technology developed by the authors [2] is also used in the prototype system of this research to closely supervise the operations that lead to obtaining the benefits of LAS.

Current studies focus on real-time data acquisition and improving simulation input modeling, which involves finding statistical distributions of the model input parameters, such as the durations of different activities [14]. For instance, Song et al. [14] used Global Positioning System (GPS) technology to capture required data, such as truck hauling time, and update a simulation input model for LAS of asphalt hauling and paving projects. These simulation systems commonly have two characteristics: first, they usually model repetitive operations, and second, the final output of these operations is one or (rarely) a few limited products. This paper deals with simulating a steel fabrication shop, in which the operations are repetitive while each product (i.e., steel piece) is typically unique. This uniqueness means the time required for processing each steel piece varies. Estimating processing duration is dependent on productivity; the degree of precision depends on the nature of the work and is influenced by several factors. The relationship between these factors and the processing duration/productivity cannot be demonstrated in an accurate and clear manner, increasing the difficulty of estimating the steel piece processing activity durations which are used for updating the simulation input model. A well-structured Artificial Neural Network (ANN) model, which has an optimal structure regarding layers and nodes, is capable of learning from data sets and reliably approximates any complicated relationships between dependent and independent variables [18]. ANN models can also handle moderate amounts of noise, which is common in the historical data, and can generate knowledge from defective or noisy data [19]. ANNs have been widely used for modeling productivity in construction; for example, concrete construction productivity [20], formwork production rates [21] and pipe spool fabrication productivity [22]. ANNs have

also been exploited in this research to intelligently generate process durations for each steel piece to be manufactured, considering influencing factors. A framework is proposed to integrate a real-time actual data collection system for steel fabrication projects with an intelligent input data generation system and with simulation models, which utilizes the as-built data for updating input models and improving the simulation results for LAS.

III. LOOK-AHEAD SCHEDULING USING SIMULATION TECHNIQUE

In steel fabrication projects, LAS involves a number of uncertain factors and constraints. No project can be started earlier than a given date due to the limitations regarding the availability of required material, space and equipment. Each project should be delivered by a certain date depending on client demand and the conditions of the erection site. The scheduler should also take into account the limits on other resources such as skilled workers, cranes and active stations in the steel fabrication shop.

A typical steel fabrication project may contain a few hundred steel pieces, which makes using traditional techniques such as the Critical Path Method (CPM) a time-consuming and tedious exercise. Moreover, in the case of any deviation from the baseline or changes in resource availability, adjusting the schedule would be very difficult. Computer simulation is a powerful technique to efficiently react to system changes and generate updated schedules. Simulation is used here as the underlying technique to model the fabrication shop and resources and activities required to

process steel pieces. To be effective, the simulation model should be updated based on the most recent system changes. Then, the impacts of these changes need to be observed by the model for modifying the LAS. To address this, this paper presents an intelligent and integrated simulation system based on the framework previously developed by the authors for automated and integrated project monitoring and control [2]. Several components of the framework established using the HLA infrastructure have been modified and the whole system is enhanced by adding intelligence for reliable look-ahead scheduling purposes. An as-planned database, as-built data acquisition, discrete event simulation, a steel fabrication process knowledge base, a calendar, and an intelligent adjuster are the major components of the proposed system (Fig. 1). HLA provides a reliable infrastructure for efficient integration of all the components of the LAS system. Interoperability, reusability, flexibility, and system speedup [2] are some advantages of utilizing HLA as the backbone for the proposed LAS system.

To have an effective LAS system, the following steps must be taken. First, the process of the steel fabrication should be well investigated and a simulation model based on that is established. For each project a baseline schedule is defined by a scheduler. During the execution course of the project, real-time data is collected from the fabrication shop and utilized to update the simulation model so that it reflects the dynamic nature of the project environment. Once the initial state of the simulation model is set, it can be used for experimenting with different scenarios and an updated LAS can be generated based on the simulation results.

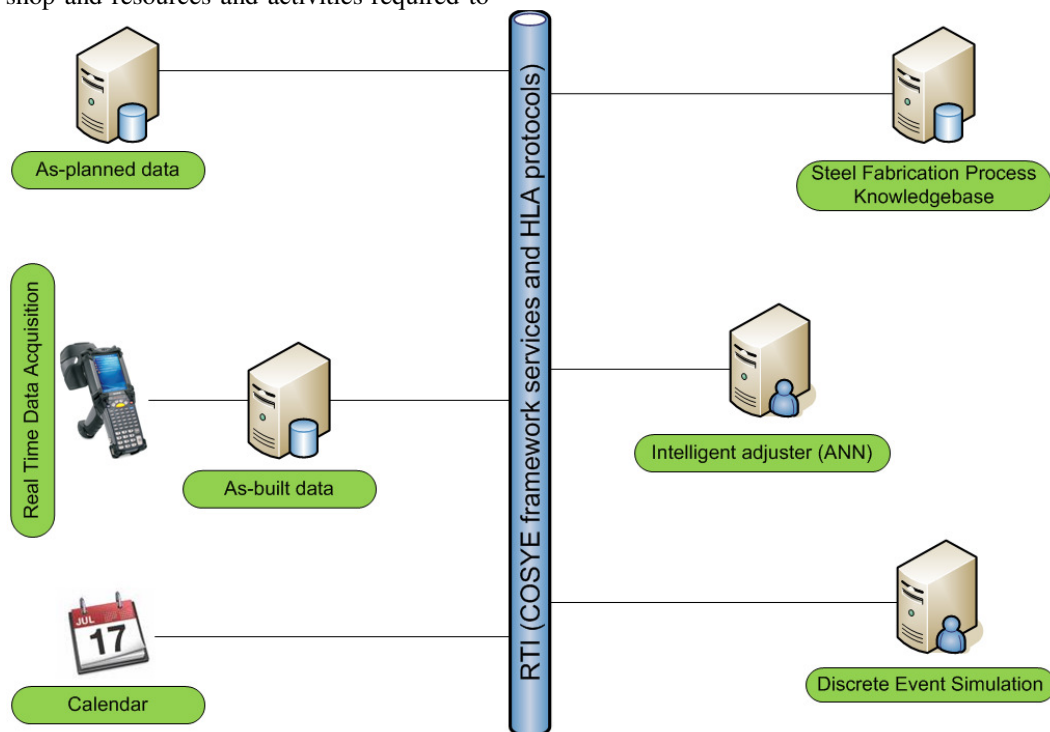


Figure 1. Integrated LAS system- a modified version of the model originally proposed by the authors[2]

A brief review of the steel fabrication process as well as the components of the proposed system is presented in the following sections to provide the reader with an overview of the research topic.

A. Steel Fabrication Process

A typical steel project consists of a number of steel pieces, such as beams, columns, or trusses, with different dimensions and specifications. Fabrication of steel pieces starts with the detailing area. In this area, the components of a steel piece are cut and/or punched according to the engineering design. Cut components are transferred to the fitting area to be fitted. Fitters bring the components together using tack welds to form the steel piece. Once inspected, the fitted piece is sent to the welding area where the welders weld the piece according to the provided specifications. Another inspection happens once the welding is done. If required, the piece is sent to the painting area, otherwise the piece is ready to be shipped to the erection site (Fig. 2).

Each area in the fabrication shop is composed of several stations which makes it possible to have several pieces processed in each area simultaneously. Steel pieces are transferred by rail carts or cranes depending on the situation. If a piece must be processed in a working area but there are not enough resources available to process that piece, it is piled in a certain storage area and waits until the required resources are available.

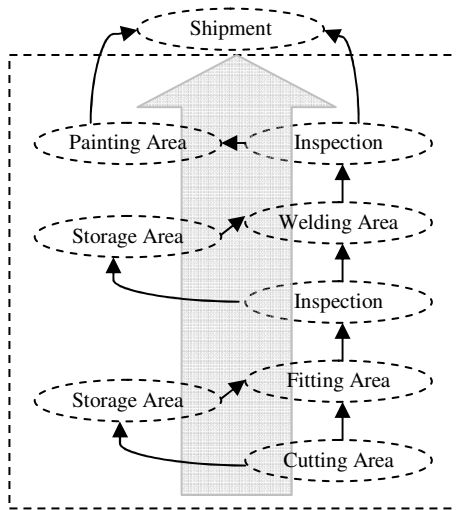


Figure 2. Steel fabrication process

Rework will be necessary if a piece is rejected by an inspector.

B. Components of the Proposed System

The backbone of the proposed system is the High Level Architecture (HLA) which has been discussed in more detail in the next section (i.e., System Implementation).

Some components of the proposed system such as Discrete Event Simulation, the calendar, and real-time data capturing have already been developed and detailed information about these components can be found in [2]. A

brief explanation of those components is also provided below.

B1. Real-Time Data Capturing

As in [2], Radio Frequency Identification (RFID) technology has also been used in this research to collect real-time data. RFID tags are put on steel pieces and the locations of the tagged pieces are tracked using portable RFID tag readers. The location tracking also captures the time a piece enters each area and the time it leaves that area. These data are then interpreted to provide project performance data, project progress, and activity duration in the steel fabrication process knowledge base component. Inter-process communication between the tag readers and the as-built database occurs via Transmission Control Protocol over Internet Protocol (TCP/IP).

B2. Steel Fabrication Process Knowledge Base

The real-time data acquisition system generates raw data. Useful performance data, such as man-hours spent on fitting or welding each piece, project percent complete, production rate and so on need to be extracted from these raw data to be used for updating LAS. Interpretation of these raw data can be automated by correlating the location of a steel piece with fabrication events and activities based on the experts' knowledge regarding the process of fabrication. A comparison between the location of a steel piece and pre-defined areas discloses meaningful information about the fabrication operation. For example, the entrance of the steel piece into the fitting area is recorded as a start-fitting event and exiting the fitting area is considered as an event called end-fitting. Once done, it is time to extract activity information from the event data. Generally speaking, each activity is begun by an event and is finished by another event. So, for the previous example, the duration of fitting activity for each steel piece can be calculated considering the start- and end-fitting events. To be effective, the gained knowledge should be managed properly in terms of capture, arrangement and retrieval of knowledge. To enforce that, knowledge bases are frequently used by the practitioners and researchers. As an example a process knowledge base for asphalt hauling is developed in [14]. A sample hierarchical structure of the required knowledge for structural steel fabrication data interpretation is presented in Table I.

TABLE I. SAMPLE ELEMENTS OF THE STEEL FABRICATION PROCESS KNOWLEDGE BASE

Area	Action	Event	Activity
Fitting Area	Enter	Start fitting	Fitting steel piece
Fitting Area	Leave	End fitting	
Welding Area	Enter	Start welding	Welding steel piece
Welding Area	Leave	End welding	
...

Different techniques can also be used to calculate other performance data. For example, the progress of each piece is determined by translating piece location to percent complete using the rule of credit based on expert knowledge [2]. For instance, the experts may consider piece fitting as 40%

progress in the fabrication phase. Project percent complete can thus be calculated by summing up the weight of each piece times its progress, all divided by the weight of the project.

B3. Discrete Event Simulation

This component is a modified and improved version of the discrete event simulation (DES) model of steel fabrication shops developed earlier [2]. Modeling the fabrication shop and prediction of the behavior of the fabrication shop is not based on mathematical models and analytical solutions. Discrete event simulation was utilized for this purpose due to the fact that simple closed form analytical solutions are not available for the modeling steel fabrication process. However, the DES federate has the capability to incorporate any available mathematical or analytical solutions.

To be effective, the DES component of the proposed LAS system should be updated in a timely manner to reflect changes in the fabrication shop's environment. The proposed DES is a self-adjustive component that exploits the captured actual real-time data to update its input models. The initial state of the simulation model is set based on the most recent data. The actual data can also be used to generate updated distributions that are substituted with the earlier input model. The intelligent adjuster is a component that takes care of this responsibility. It automates the input-model update procedure with no slow and error-prone human involvement.

Scheduling is performed in DES model based on the earliest-due-date (EDD) dispatching rule, such that the project with the earliest due date is selected and processed first. The scheduling engine of the DES model enables automated project schedule updates to be generated and stored in an MS Access database. The DES model is also capable of performing earned value analysis, and cost and schedule performance indices can be calculated for all the steel pieces.

B4. Intelligent Adjuster

Updating input models can be carried out by external prediction models [23]. The proposed intelligent adjuster is an autonomous Artificial Neural Network (ANN) component that is trained with the actual data available in the aforementioned steel fabrication process knowledge base to generate updated distributions, e.g., regarding duration of different activities required to process each piece of steel for the simulation input model. While it is difficult and sometimes not feasible for estimators to consider in their estimations all the influencing factors for a huge number of steel pieces with different dimensions and specifications, artificial intelligence has the capability to overcome this issue and forecast and update the distributions to be used in the steel fabrication simulation model. In this way, the accuracy of the simulation model is enhanced by explicitly modeling uncertainty variables and their impacts on the performance of the fabrication shop and ongoing projects.

B5. Calendar

Schedules are highly influenced by day shift hours, night shift hours, overtime hours, and holidays. The user defines these parameters within the calendar federate which sets related initial values for the DES model [2].

IV. SYSTEM IMPLEMENTATION

A) Infrastructure

A prototype system has been developed for look-ahead scheduling of steel fabrication projects. The proposed system implements the Construction Synthetic Environment (COSYE) software environment [24], an HLA-based simulation environment developed at the University of Alberta. HLA is a reliable infrastructure for integrating different components of a simulation model, called federates, into a single distributed simulation model, referred to as a federation [25]. HLA promotes interoperability between simulations and aids the reuse of models in different domains, which leads to reduced time, cost and efforts to create a synthetic environment for a new purpose [25]. Development of simulation models of different construction applications significantly benefits from these features of HLA because these simulation models usually share a number of common components [2]. HLA can be characterized by three main components [26]: HLA rules, the HLA interface specification, and the Object Model Template (OMT). The OMT provides a common framework for data exchange between different federates. The run-time infrastructure (RTI) is a piece of software that complies with the HLA specifications and provides services such as synchronization, communication, and data exchange between federates.

COSYE is composed of an RTI, an environment that is optimized for development of federations in different construction domains, and a suite of generic modeling elements. During run time, COSYE provides necessary communication, information exchange, and data sharing protocols using an RTI that assures synchronization, coordination and consistency between different federates.

In this prototype system, the primary project LAS (baseline) is prepared by a scheduler and is stored in a MS Access database. Captured real-time actual data are also stored in a MS Access database. The base model of the DES component (federate) was developed within the Symphony.NET simulation environment [27] for modeling steel fabrication operations. Figure 3 depicts the interface for the DES federate [28].

B) Factors affecting the intelligent adjuster's forecasting

The process knowledge base, demonstrated in Table 1, is used to extract fabrication activity information from the actual data and feed the intelligent adjuster component.

Fitting and welding operations are the critical operations in the structural steel fabrication and usually take more than 80% of the available resources on average. In the proposed system the intelligent adjuster is composed of two Artificial

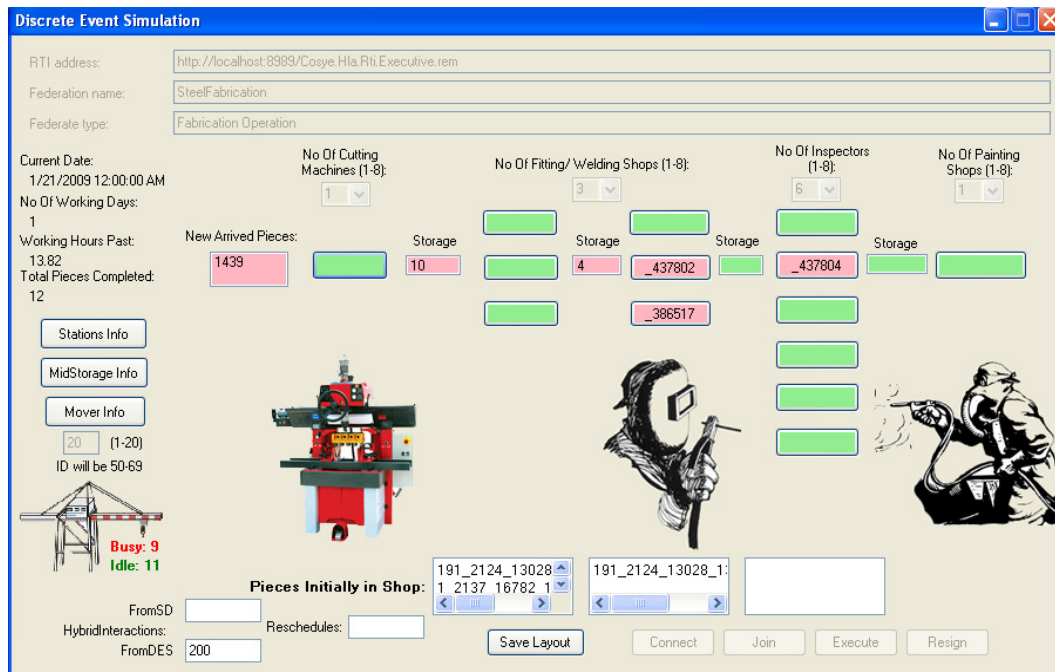


Figure 3. The DES federate [28]

Neural Network (ANN) models and predicts the steel fitting and welding productivity/durations based on the complexity of each steel element and other influencing factors. Influencing factors can be divided into two major categories: the steel piece itself and the fabrication shop environment. Song et al. [29] proposed four piece-oriented influencing factors, such as number of fittings, number of cutouts, piece length, piece weight, and two influencing factors regarding the fabrication shop environment for the fitting operation, such as worker rank and work shift. There are two concerns regarding the proposed piece oriented factors. Firstly, although it is clear for beams and columns, piece length is a vague concept for other steel pieces such as frames and stairs. As an example, for a square steel frame, one person may consider the side length as the piece length while another person may use the diagonal of the square as the piece length. Piece dimension is an important factor because piece movement and piece flipping in each operation are highly affected by this property of steel pieces. However, piece weight commonly has a close and positive correlation with piece dimension (i.e., the bigger the piece, the greater its weight). This means that by considering piece weight as an influencing factor the piece dimensions are implicitly addressed. Secondly, the number of fittings and cutouts are two influencing factors in the fitting operation but not necessarily for the welding operation. Two different approaches can be taken considering the influencing factors. One approach is to define the factors for each specific operation, while the other approach is to define general influencing factors that can be used for different operations in steel fabrication. Within this research the second approach has been taken because of its universality and usage in the whole fabrication process. Therefore, the influencing factors considered in this research that are related to the

characteristics of the steel piece include piece complexity – replacing the number of fittings and cutouts – and piece weight; the ones that are related to the shop environment are the rank of the workers and the working shift in which the pieces are manufactured.

Having said that, the inputs of the intelligent adjuster are the weight of the steel element (piece/assembly), the shift in which it has been fabricated, the rank of the worker who has processed that steel element (the higher the rank the more experienced the worker) and piece complexity. Piece complexity is represented by a parameter called “complexity factor.” “Complexity factor” refers to the number of the components in each steel piece. For instance, the steel beam shown in figure 4a is composed of an I shaped beam and 5 stiffeners. Thus, there are 6 components forming that steel piece which results in a complexity factor equal to 6.

Steel pieces differ, sometimes significantly, regarding their complexity factors. In other words, while some steel pieces are fairly simple (e.g. Fig. 4a), some pieces can be considerably more complicated (e.g., Fig. 4b). The complexity factor can also be calculated for each division with the same concept, i.e., total number of steel components divided by the number of steel pieces forming the division. A template was also developed to automatically capture complexity factors and weight of steel pieces from 3D models (Fig. 5) of steel projects. These 3D models use Building Information Modeling (BIM) which is a common way to construct a building virtually before building it in the real world, bringing the structures from concept to reality [30]. Automatically capturing information from 3D models with minimum human involvement guarantees high-quality data with great speed for data analysis purposes.

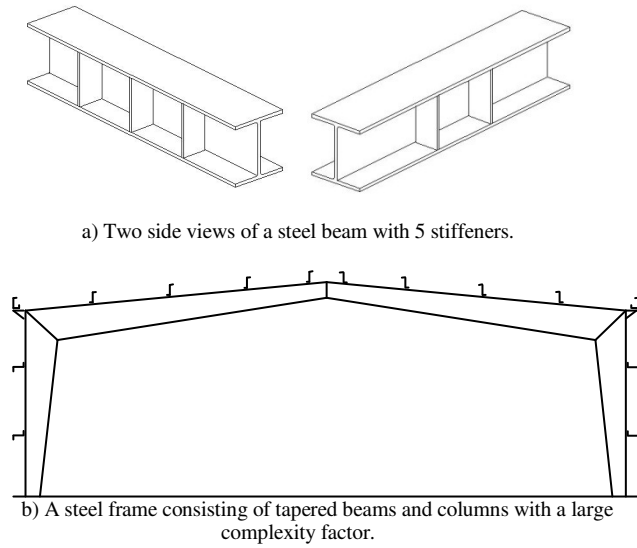


Figure 4. Sample of structural steel pieces with different complexities

A sample of data captured automatically from a 3D model by the developed template is represented in Table II.

The intensity of complexity is an indicator that determines how complicated a steel element is (i.e., piece complexity) and has a direct relationship with the complexity factor. It is one of the input variables utilized for training the intelligent adjuster and is defined as in Table III.

TABLE II. SAMPLE OF DATA CAPTURED BY THE DEVELOPED TEMPLATE FROM 3D MODELS

Piece ID	C.F.*	I.C.**	Weight(kg)
50A1	12	4	582
50A2	17	5	555
50A5	10	3	529
50A7	17	5	539
50A4	10	3	529
50A8	17	5	542
50A6	11	3	519
50A15	19	5	293
50A16	9	3	280
50A20	9	3	132
50A18	7	2	137

* Complexity Factor
 **Intensity of Complexity

TABLE III. DEFINITION OF THE INTENSITY OF COMPLEXITY

I.C.	Definition	Explanation
1	Not complicated	$1 \leq C.F. < 4$
2	moderately complicated	$4 \leq C.F. < 8$
3	complicated	$8 \leq C.F. < 12$
4	very complicated	$12 \leq C.F. < 16$
5	extremely complicated	$16 \leq C.F.$

C) Training the intelligent adjuster

The intelligent adjuster uses two back-propagation networks, each with 4 input nodes, one hidden layer, and one output node at the output layer.

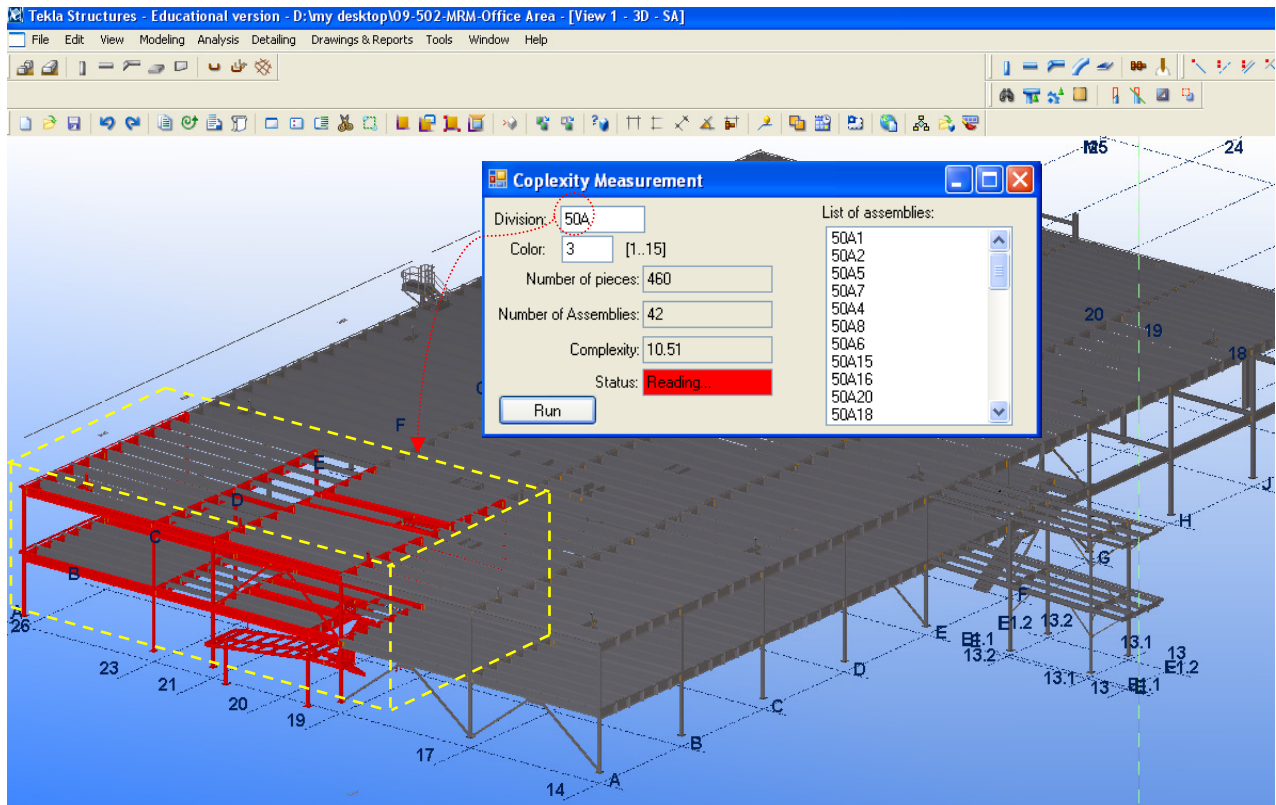


Figure 5. Developed template for capturing complexity factor from 3D models

The number of hidden neurons for the networks is calculated with the following equation [31]:

$$H_n = 0.5 \times (I + O) + \sqrt{P} \tag{1}$$

Where:

H_n : Number of hidden neurons

I: Number of inputs

O: Number of outputs

P: Number of patterns

“Neuroshell 2” [31] was used to train the networks. 114 fitting data points and 61 welding data points were captured by the real-time RFID data capturing system during a two-week time/case study used for training and validating the ANN models. For the fitting operation, 92 data points were randomly selected for training and 22 data points were used for testing. The learning rate and momentum of the fitting ANN model were set to 0.1. The initial weight of the links within the ANN model was set to 0.3 and numeric range of the linear scaling function used for the input layer was [-1,1]. For the welding operation, the number of training and testing data points were 49 and 12 respectively and the initial settings for learning rate, momentum etc. were similar to the settings of the fitting ANN model. The labor-driven nature of the steel fabrication process may lead to variance in productivity or activity duration even for similar steel pieces processed with laborers with the same rank and in the same shift. In this research one assumption is that such a variance is trivial; if that is not the case some techniques such as data filtration or using averages of the data can help in compensating for variances in the data. Sample actual data regarding welding operation that were used for training the intelligent adjuster are presented in Table IV.

TABLE IV. HISTORICAL DATA USED FOR TRAINING THE INTELLIGENT ADJUSTER

Weight (kg)	Shift (Day:1-Night:2)	Rank	I.C.	Duration (Minutes)
519	1	2	3	109
87	1	1	4	163
122	1	2	2	55
919	1	1	5	197
549	2	2	3	160
111	1	1	3	90
973	2	2	4	218
1250	1	3	4	121
...

The training results regarding duration of fitting and welding operations (in minutes) are summarized in Table V. There are several factors that may affect the maximum absolute error in terms of duration prediction presented in Table V. For instance, once a fitted or welded piece is rejected by an inspector, it requires rework, and the activity duration is extended and is greater than a situation in which rework is not required. Missing components of a steel piece or unclear or impractical drawings are other examples that extend the normal fitting/welding durations. With that said,

and considering the wide duration ranges in fitting and welding data sets (i.e., from 10 to 290 minutes for the fitting data set and from 20 to 352 minutes for the welding data set), the trained networks are considered proportionately accurate in forecasting the fitting and welding durations with an acceptable margin of error.

TABLE V. INTELLIGENT ADJUSTER TRAINING RESULTS

Item	Fitting	Welding
Patterns processed:	114	61
R ² :	0.89	0.87
Mean absolute error:	13.46	26.14
Min. absolute error:	0.02	0.11
Max. absolute error:	73.20	53.00
Correlation coefficient r:	0.95	0.94

Two indicators, including R Squared (R²) and the correlation coefficient (r), usually used for interpreting the neural network models, are also presented in Table V. As indicated in Table V, the R² values for the fitting and welding operations are 0.89 and 0.87 respectively. According to the network training results presented in Table V, the correlation coefficients for the fitting and welding operations are 0.95 and 0.94 respectively, which implies a strong positive relationship between the model outputs and the actual outputs for these operations.

Figure 6 shows the trained network predictions against the actual welding duration trained values for the welding data points.

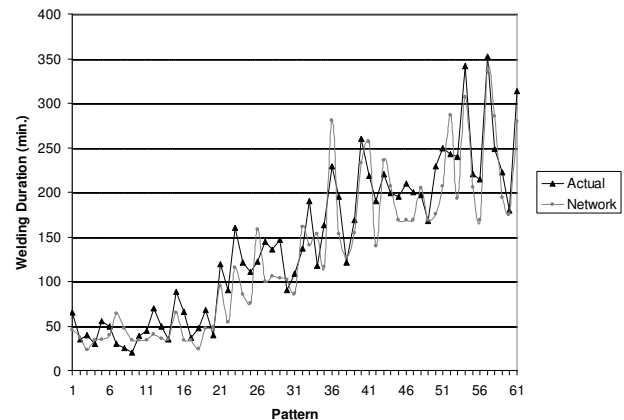


Figure 6. Actual vs. forecasted welding duration for data points

The trained ANN models were compiled as VB.NET code and used for developing the intelligent adjuster federate. This federate is capable of generating the distributions and other scheduling variables, such as productivity rate, based on the attributes (e.g. weight, complexity intensity, etc.) of each steel piece. An example of the generated scheduling variables is shown in Figure 7. This figure is a snapshot of an interface developed to provide managers with an intuitive report on the forecasted trend of productivity rates for fitting and welding activities within a 3-day time interval ending at

the date selected by the user. Such information can be a heads-up for impending deviations from desired values. The generated distributions then will be fed into the DES federate to improve its results. If required, the user can modify the influencing factors and experiment with different scenarios with the simulation model to find the best corrective actions to converge on the project goals.

V. CASE STUDY

A case study, the construction of an administrative office, was carried out to verify the feasibility and accuracy of the implemented simulation-based LAS system for steel fabrication projects. Because of the size of the building, the whole project is divided into 57 “divisions.” Each division itself includes several hundred steel pieces, including beams, columns, stairs and frames. The baseline schedules for all the divisions were prepared by the scheduler and stored in the baseline database. The data acquisition system was set up in the fabrication shop. The major elements of the data acquisition system are RFID tags, a tag reader, and a router connected to a computer. Data capturing began with the launching of the project in the shop (Fig. 8). The DES federate models four activities – cutting, fitting, welding, and painting. The resources required for this model include active stations (which correlate with the number of operators) in different areas, cranes and rail carts, inspectors, and storage areas.

Usually, several divisions are processed at the same time in a fabrication shop and certain stations in each area are

assigned to each division. The data capturing was carried out for all the steel elements that were being processed in the fabrication shop. In this way, scheduling information for the project level as well as the performance information (such as production rate at different areas) at the shop level was determined.

The actual data collected during the case study were used to examine the accuracy of the simulation model. However, during the case study several outstanding discrepancies were captured. First, some fitting and welding stations shut down due to the fact that a number of fitters and welders were laid off during the case study. Second, the actual process time in each station was longer than expected in many cases. Third, the production rate predicted by the simulation model was significantly greater than what happened in reality. These discrepancies detract from the utility of the LAS and mean that the simulation model needs to be properly modified and updated in some aspects to address these deviations.

Updating the simulation model is easy with regard to changing available resources (e.g., the number of active stations), but with variables such as process time and production rate, it is less straightforward. Variances in the process time and production rate can be caused by faults in estimation, external factors that were not considered in the simulation model, or both. While the faults in process time estimation are usually covered by the actual data, considering the effects of the external factors in the simulation model is a difficult task. For example, during the course of the case study, a number of workers received

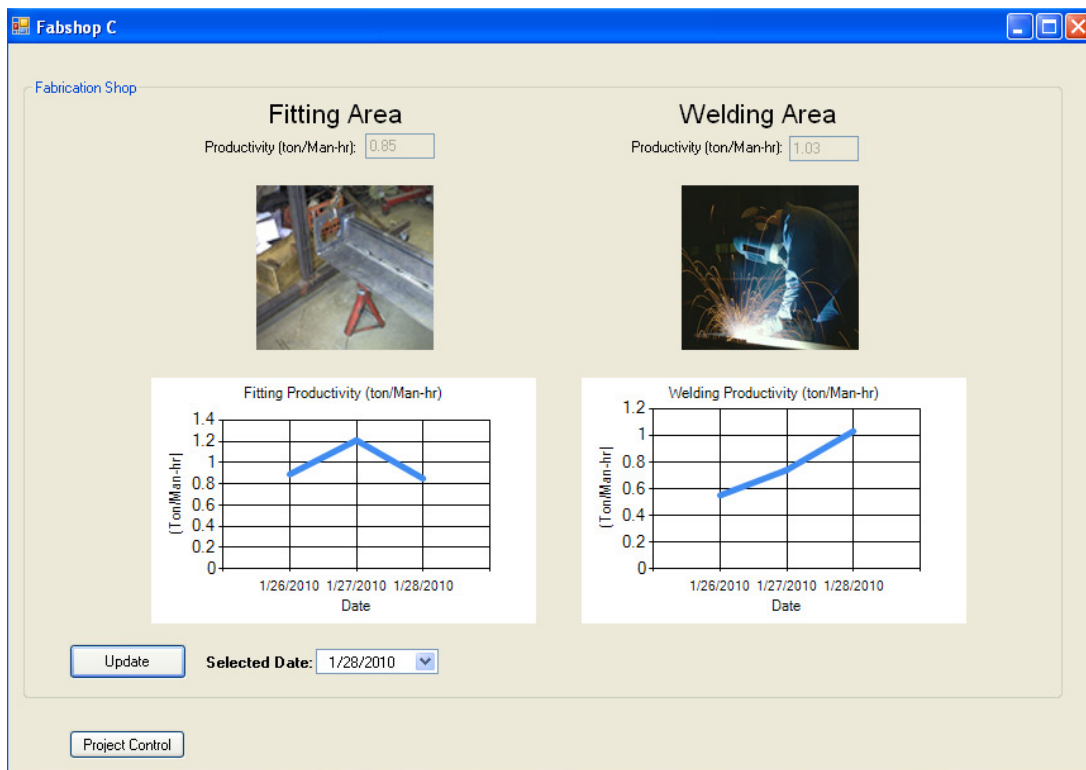


Figure 7. Fitting and Welding production forecasted by the intelligent adjuster component for the fabrication shop.



Figure 8. Collecting actual data using RFID technology

termination notices due to the recession conditions. After being informed that their employment will cease by the next month, the productivity of these workers was far lower than what was estimated. The arrival of a new project with a higher priority that had not been considered in the master plan was another issue that meaningfully affected the available resources (e.g., raw material), shop performance and LAS for ongoing projects during this case study. A thorough tracking of the variances regarding schedules and budget (i.e., assigned man-hours) resulted in determining seven major factors causing variances in the studied fabrication shop (Fig. 9). Once these factors are tracked, they need to be addressed to improve the performance of the ongoing projects and the fabrication shop itself. Project managers and foremen try to make improvements in different areas that cause deviations and variances over the course of the fabrication, but it is still a major concern for them to have reliable LAS for different projects which take into account current situation in the fabrication shop. This is the benefit of the LAS system which has been developed, which enables users to have updated LAS automatically generated based on the most recent actual data. An updated LAS is a sound foundation for decision making and system analysis. Sample results of the simulation model, based on 30 simulation runs, regarding LAS based on the actual data are shown in Table VI. The simulation results in Table VI represent four divisions including 321 steel pieces that originally were planned to be fabricated in the specified time interval (i.e., from January 18 – 27, 2010). Scheduled start and finish dates come from the project

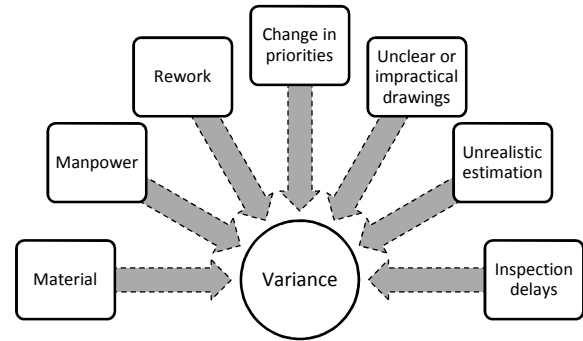


Figure 9. Major factors causing cost/schedule variance in the case study

baseline defined by a shop manager and two foremen, each with more than 15 years of experience. The calculated start and finish dates are the simulation output, generated based on the current shop conditions and the activity duration distributions forecasted by the intelligent adjuster for the pieces planned to be manufactured within the stipulated period of time. A comparison between the actual finish dates and the estimated finish dates generated by the people involved in scheduling, and what the developed intelligent system generated, results in determining estimation errors. Estimation error analysis reveals that the intelligent system could generate more reliable managerial information and LAS. As an example, for division 52A, human error regarding the finish date was 11 days, while the intelligent system had an error of 4 days. The average absolute estimation errors for the 4 divisions shown in Table VI was 9 days in the case of human judgment, while the intelligent system’s estimation had an absolute error of 1.75 days on average. This may be attributable to the fact that the intelligent system generates schedules based on the recent conditions of the dynamic environment of the fabrication shop, perceived influencing factors and their combined interactions, while human beings are seldom able to consider all of these parameters in scheduling. It should be noted that a shortage of actual historical data that could be used for training the intelligent adjuster limited the accuracy of the developed system. Even though the performance of the developed LAS system is quite promising, having more actual historical data can enhance the intelligent adjuster forecasts and subsequently improve the accuracy of the simulation results.

TABLE VI. SAMPLE RESULTS OF THE SIMULATION FEDERATE

Division ID	No. of pieces	Scheduled Start Date	Scheduled Finish date	Calculated Start date	Calculated Finish Date	Actual Finish Date	Error in Estimating Finish Date (days)	
							Human Estimator	Intelligent LAS system
52A	64	18/01/2010	22/01/2010	18/01/2010	29/01/2010	1/2/2010	11	4
51A	34	19/01/2010	25/01/2010	19/01/2010	29/01/2010	29/01/2010	4	0
5A	103	19/01/2010	27/01/2010	20/01/2010	4/2/2010	5/2/2010	9	1
50A	120	21/01/2010	27/01/2010	25/01/2010	10/2/2010	8/2/2010	12	-2

CONCLUSION

Look-ahead scheduling of steel fabrication projects that considers projects' constraints as well as the fabrication shop's constraints is very complicated. This paper implements an intelligent and integrated simulation-based LAS framework for an actual case study in a steel fabrication shop. The system that was developed utilizes RFID technology to capture as-built data. As-built data along with the as-planned data are fed into the system; raw actual data are translated to meaningful data, and an intelligent component generates/forecasts essential scheduling variables based on the actual and historical data for each steel piece, considering several piece-oriented and environmental influencing factors, and updates the simulation model to allow it to produce reliable look-ahead schedules. The proposed system is expanded by employing High Level Architecture (HLA). In this way, the model is split into several components that are linked together in a well-structured format.

Unlike traditional scheduling methods that are static and time-consuming to update, the capability of the proposed system to dynamically and intelligently incorporate the most recent project data and changes in the fabrication shop environment can improve the accuracy of LAS and reduce input modeling burdens on end users.

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