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AI-ASSISTED PDF EXTRACTION AND RULE-BASED PRODUCTION TIME ESTIMATION IN STRUCTURAL STEEL ASSEMBLY USING HISTORICAL PRODUCTION DATA

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Abstract: Offsite construction improves quality control, accelerates project completion, and minimizes disruptions at the construction site compared with traditional onsite construction methods. Within this paradigm, steel fabrication plays an essential role by enabling structural elements to be produced under controlled conditions, thereby increasing precision and supporting a more efficient assembly process. Despite these advantages, inaccurate production time estimation in steel fabrication plants remains a persistent challenge, contributing to cost overruns, project delays, suboptimal resource allocation, and difficulties in short-term production planning. A primary driver of this inaccuracy is an interoperability gap: the detailed parametric data required for reliable time estimation is typically locked within unstructured design files, such as 2D shop drawing PDFs, making it inaccessible for automated prediction models. To bridge this gap, the present study proposes a structured, design-driven workflow that extracts and leverages latent information from shop drawings to estimate structural steel assembly times. The methodology operates in two sequential stages. First, an AI-assisted extraction framework parses unstructured PDF data into structured inputs, isolating key assembly variables including member sectional dimensions, weight, crane handling requirements, and the quantity of attached components. Second, these inputs are integrated into a rule-based computational model that calculates production time using historical productivity rates and logic-driven algorithms. By creating a direct pipeline between static design documentation and dynamic production planning, this approach establishes a practical foundation for early-stage estimation and look-ahead scheduling. A proof of concept using a representative shop drawing confirms the workflow's feasibility. The findings demonstrate that this method provides a scalable, consistent, and practically implementable framework for estimating production time, laying the groundwork for advanced scheduling and decision-support systems in steel fabrication.

Keywords: **Structural Steel Fabrication; Steel Assembly; Time Estimation; AI-Assisted Data Extraction; Rule-based Estimation; Shop Drawings; Historical Production Data.**

1 INTRODUCTION

Accurate production time estimation is essential for effective planning and resource management in structural steel fabrication (Aghajamali, Metvaei, Suliman, et al. 2025). In off-site construction, where structural components are manufactured in controlled environments prior to installation (Aghajamali, Lemouchi, et al. 2024; Metvaei et al. 2025), reliable estimation plays an important role in supporting productivity, scheduling, and supply chain coordination. In practice, inaccurate estimates frequently result in cost overruns, schedule delays, and inefficient use of labor and equipment (Vahdani et al. 2016). Therefore, improving estimation fidelity has become a critical priority for enhancing project planning and operational efficiency in the construction industry (Aghajamali et al. 2026).

Because project success depends heavily on the accurate prediction of activity durations and productivity rates (Sadatnya et al. 2023), various approaches have been developed to improve estimation accuracy. These include methods based on structured digital information and artificial intelligence techniques such as regression analysis, expert systems, and machine learning (Aghajamali, Metvaei, and Lei 2025; Gurmu and Ongkowijoyo 2020; Yi and Chan 2014). However, these advanced predictive models generally require organized inputs and pre-established data models, prerequisites that are rarely available in dynamic, traditional fabrication environments (Seidel et al. 2023).

A major challenge in steel fabrication is that critical estimation-relevant information is often embedded in structural steel shop drawing PDFs in an unstructured and static format. Parameters such as member sectional dimensions, length, weight, number of attached parts, and handling requirements are visually present in the drawings, but they lack the machine-readability required for direct use in automated estimation workflows. As a result, fabrication planning remains heavily reliant on manual interpretation of shop drawings and experience-based judgment, which introduces subjectivity, can reduce consistency, and limit efficiency. More broadly, extracting useful information from unstructured documents is a pervasive bottleneck in industrial environments because large volumes of data are stored in formats such as scanned PDFs (Khurana et al. 2023; Saout et al. 2024a). Traditional processes often rely on manual efforts to locate and extract the required information, which is time-consuming and error-prone. Although automated approaches such as Optical Character Recognition (OCR), natural language processing (NLP), and machine learning have been proposed (Avei et al. 2024; Khurana et al. 2023), these methods often struggle with the complex spatial relationships, diverse layouts, noisy data, and inconsistencies commonly found in real-world industrial documents (Saout et al. 2024b). However, recent advances in large language models (LLMs) have created new opportunities for overcoming these interoperability gaps by extracting structured information from unstructured sources through context-aware prompt-based interaction (Dong et al. 2024; Huang et al. 2022; Tang et al. 2023).

In response to these challenges, this study proposes a prompt-based, AI-assisted workflow designed to bridge the gap between static design documentation and active production planning. The methodology extracts key assembly information from structural steel shop drawing PDFs and leverages the extracted outputs for production time estimation. In the proposed workflow, the prompt plays a central role in guiding the extraction of estimation-relevant attributes from unstructured drawing content and converting them into structured, machine-readable inputs. These extracted attributes are then transferred to a rule-based computational estimation tool, where production time is calculated using predefined logic and average productivity rates derived from historical production data collected from a fabrication shop. The purpose of this workflow is to transform latent design information into estimation-ready inputs that support faster, more consistent, and more scalable production planning in steel fabrication environments. By estimating production time directly from shop drawing information, the workflow also establishes a vital data pipeline between design data and future look-ahead scheduling for multi-component project deployment.

2 LITERATURE REVIEW

Construction productivity reflects how effectively resources are allocated and utilized to maximize project output (Council et al. 2009). Since construction projects depend on valuable and costly resources such as labor and equipment, precise planning is essential to ensure efficient implementation (Sarker et al. 2012). In the context of offsite steel fabrication, the substantial capital investment required for plant operations makes optimized scheduling and multi-shift efficiency paramount. To improve construction efficiency, researchers have increasingly adopted data-driven approaches that leverage machine learning and advanced analytics to automatically develop predictive models(Aghajamali, Metvaei, et al. 2024) . As a knowledge management tool, a predictive model helps extract actionable value from historical organizational assets (Alavi and Leidner 2001). A number of researchers have explored the effectiveness of AI models in predicting activity duration (Aghajamali et al. 2022) and defining work scope (Song et al. 2003) within construction operations. In addition, several studies have examined the use of data-driven techniques for time estimation in steel fabrication processes. For example, Aghajamali et al. (2022) addressed cycle time prediction at the station level using observed shop-floor data. These studies show that historical data play an integral role in improving estimation accuracy in fabrication environments.

Recent advances in document AI tools have created new opportunities for processing unstructured documents more efficiently and accurately. However, several challenges remain unresolved, particularly in handling document variability and improving extraction reliability in real-world industrial applications. A study by Liu et al. presented a method for segmenting low-level document structures through visual prompting (Liu et al. 2023). In this method, adjustable parameters are used to extract visual information from each image, including region segmentation, object recognition, and blurred-pixel detection. Nevertheless, the strong reliance on tunable parameters means that labor-intensive manual adjustment may be needed for each new type of document, severely limiting the method's scalability (Liu et al. 2023). In document extraction systems, the success of information extraction depends greatly on the prompt optimization method being used. Recent research has identified several strategies for improving performance. For example, Sun et al. (2023) presented an automated approach to prompt optimization using guided hints. Furthermore, according to Zhou et al. (2022), LLMs can perform prompt engineering tasks with human-level effectiveness, opening pathways for more adaptive extraction systems.

However, existing studies in document information extraction and construction productivity estimation are often treated as isolated research areas. While document AI methods focus on extracting structured information from unstructured data, traditional estimation approaches typically rely on the assumption of predefined, structured datasets. There is a critical lack of research that integrates automated information extraction from static shop drawing PDFs with practical estimation methods, such as rule-based approaches supported by historical production data. To address this gap, the present study positions AI-assisted shop drawing extraction and rule-based production time estimation as connected components of a single workflow rather than independent tasks. In this workflow, extracted shop drawing attributes, such as profile, length, weight, sectional dimensions, and crane-related requirements, are transformed into estimation-ready variables that can be directly compared with historical production records. This unified workflow bridges the interoperability gap between unstructured shop drawing documents and structured production planning data in steel fabrication environments.

3 METHODOLOGY

Figure 1 presents an overview of the proposed AI-assisted workflow for estimating production time in structural steel fabrication from shop drawing PDFs. The workflow starts with two primary inputs: the shop drawing PDF and historical production data. Relevant estimation-related attributes are then extracted from the drawing using an AI-assisted PDF extraction approach. The extracted information is subsequently transferred to a rule-based estimation model implemented in Excel, where comparable historical cases are identified and used to calculate the estimated production time. The final output of the workflow is the estimated production time for the selected assembly.

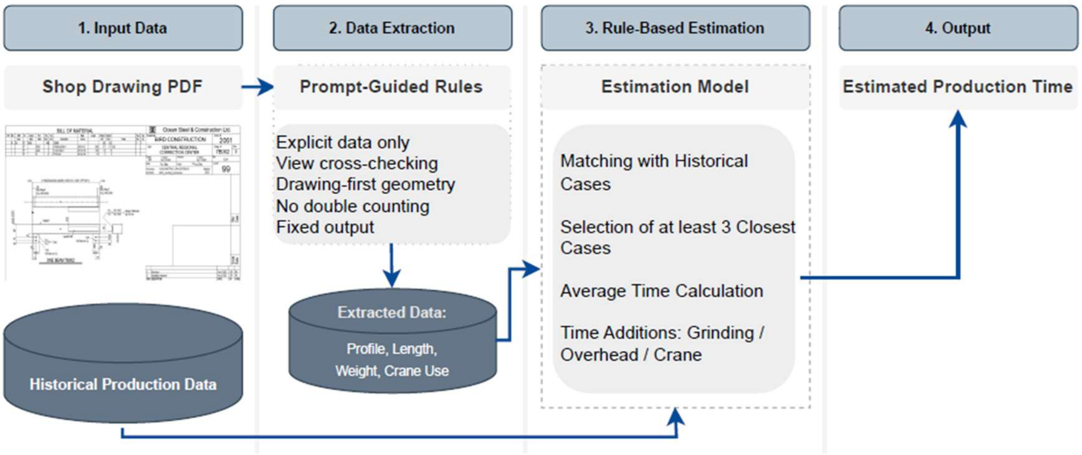

Figure 1: AI-assisted workflow for production time estimation using shop drawing PDFs and historical production data

3.1 Input Data

The proposed workflow was developed specifically for light fitting assemblies and is based on two main input sources. The first is a shop drawing PDF obtained from an industry collaborator, containing the geometric and assembly-related information required for accurate production time estimation.

The second input consists of historical productivity data collected via empirical time-study observations across several fabrication stations. The dataset is organized in a structured format and includes actual production times together with assembly-related attributes, such as part sectional dimensions, weight, and other variables affecting production duration. These historical records serve as the empirical baseline for the estimation process and are utilized by the rule-based model to identify comparable cases and estimate production time under similar past production conditions. By incorporating historical production data, the workflow links extracted drawing information with actual fabrication experience, thereby grounding the predictive model in practical reality**.**

3.2 AI-Assisted Data Extraction from Shop Drawings

The shop drawing PDF is processed using an AI-assisted, prompt-based extraction method to obtain the parameters required for production time estimation. Because the drawing content is inherently unstructured, this stage converts visually embedded information into a structured format suitable for computational use in the estimation workflow. A dedicated prompt was engineered to guide the extraction process and ensure consistent interpretation of assembly-related information.

3.2.1 LLM Model and Prompt Design

In this study, OpenAI GPT-4.5 was used as the large language model for the AI-assisted extraction stage. The model was guided through a dedicated prompt designed to extract fabrication-related information from structural steel shop drawing PDFs. The prompt defined the model's role as an expert structural steel shop-drawing data extractor and instructed it to extract only explicitly written or visually verifiable information from assembly drawings, details, sections, elevations, plan views, and bills of materials.

The most important features of the prompt include the following:

1. **Explicit extraction constraints:** The model was instructed to extract only explicitly written or visually verifiable information from the shop drawings, including part specifications such as profile type, length, weight, sectional dimensions, steel grade, quantity, and other required attributes. When information could not be confirmed from the drawing, the model was required to return NULL.
2. **Drawing-view cross-referencing:** Section, elevation, and plan views were cross-referenced to interpret the assembly and identify flip requirements for the main member.
3. **Drawing-first geometry rule:** Geometry and connection-related information were extracted from drawing views, with section views given the highest priority. The bill of materials was used only for non-geometric attributes.
4. **Double-counting prevention:** The prompt prevented duplicate counting by merging information from different views when they represented the same physical part.
5. **Fixed output structure:** The output was constrained to a consistent table format containing the fields required for the rule-based estimation model.
6. **Flip and handling logic:** The prompt included predefined rules for calculating beam flips and identifying crane-related handling requirements based on confirmed drawing evidence. Attached parts were counted as requiring crane-assisted handling when their weight was ≥50 lb or their length was ≥1500 mm.

During initial tests, some challenges were observed, particularly in extracting handling- and flip-related information. For example, in handling, early prompt versions could mistakenly count the main member because it often exceeded the weight threshold. This was addressed by clarifying that handling count applies only to attached parts and excludes the main member. For beam flipping, the main difficulty was that flip requirements depend on the physical connection faces of the main member, not simply on the location of parts along the beam. Therefore, the prompt was refined to give priority to section views and to define connection faces more clearly. These refinements improved the consistency of the extracted results, although visually complex cases may still require manual verification.

The main value of the proposed method lies in converting shop drawing information into estimation-ready variables, rather than only extracting text from PDFs. While OCR-based tools and PDF extraction packages can retrieve text, tables, or layout information, the proposed prompt-driven LLM workflow embeds domain-specific engineering rules into the extraction process. These rules support view cross-referencing, double-counting prevention, flip detection, and crane-handling identification. As a result, the extracted output is structured and directly usable in the rule-based estimation model.

3.2.2 Extraction Output and Validation

The output of the extraction stage is a structured table containing key assembly-related attributes, including contract number, assembly mark, quantity, part mark, steel grade, profile, sectional dimensions, length, weight, and handling-related fields such as flip count and crane requirement. This structured output is transferred to the estimation model as input for the production time estimation process. Although not all extracted fields feed directly into the estimation logic, only a strategic subset, such as profile, length, weight, and sectional dimensions, is used to identify similar historical cases, and crane requirement and flip count fields are used to account for handling-related time additions. In this way, the extracted shop drawing information is transformed into estimation-ready variables that directly support the rule-based production time estimation model.

A preliminary validation was conducted by processing 20 shop drawings using the developed extraction prompt and manually comparing the extracted results with the original drawings. Key fields, including assembly mark, part mark, steel grade, profile, sectional dimensions, length, weight, flip count, and crane requirement, were verified against the bill of materials and corresponding drawing views. The results were generally consistent with the original drawing information; however, errors were observed in three drawings, mainly related to flip count and crane requirement interpretation, which aligns with the known complexity of these fields discussed above. In cases where information could not be clearly verified from the drawing, the extraction rule returned NULL rather than an inferred value, consistent with the explicit extraction constraints defined in the prompt. This preliminary validation supports the feasibility of the proposed extraction approach, while a more systematic quantitative assessment will be conducted in future work.

3.3 Rule-Based Estimation Model

The structured data obtained from the extraction stage are transferred to a rule-based estimation model developed in Excel. Excel was selected for its widespread accessibility, high transparency, and seamless integration into existing industrial environments. The purpose of this model is to estimate production time by comparing the extracted attributes with similar records available in the historical production dataset.

The estimation process is carried out at the part level. First, the AI-extracted attributes of each part, including profile, sectional dimensions, length, weight, and crane-related variables, are imported into the Excel-based estimation model. For each part, historical production records are filtered by similar profile type, which is treated as a categorical exact-match criterion. The filtered records are then ranked based mainly on length and weight similarity. At least three of the closest historical records are selected as analogous cases, and the average of their observed production times is used as the base production time for that part.

This similarity-based estimation yields the required time for the light fitting operation for each part; however, some predefined time additions for operation- and handling-related conditions are also incorporated into the model to achieve the total time for the fitting station. Reviewing and grinding times are added as fixed operation-related allowances, while crane-related time is added based on the number of crane-required actions identified during the extraction stage. Each crane-required action is assigned 2 minutes, based on shop-floor observations.

The estimated assembly time is calculated using Eq. 1.

$$T_{\text{assembly}} = T_{\text{reviewing}} + T_{\text{grinding}} + (N_{\text{crane}} \times T_{\text{crane}}) + \left(\sum_{i=1}^{n} T_{\text{production}}\right) \qquad (\text{Eq. } 1)$$

Where:

- $T_{assembly}$: total estimated assembly time
- $T_{production}$: estimated production time of part i
- $T_{reviewing}$: time associated with reviewing
- $T_{grinding}$: time associated with grinding
- N_{crane}: number of crane-required actions
- T_{crane}: 2-minute allowance for each crane-required action based on shop-floor observations

4 PROOF OF CONCEPT

To demonstrate the practical applicability of the proposed workflow, a proof-of-concept case was conducted using a light fitting assembly shop drawing provided by the industry collaborator. As illustrated in Figure 2, the selected case represents a typical steel assembly in which geometric attributes, part information, and handling-related variables are required for light fitting time estimation. In the initial step, the static shop drawing PDF was processed using the AI-assisted extraction method to retrieve the estimation-required parameters. The extracted output included attributes such as contract number, assembly mark, quantity, part mark, steel grade, shape, sectional dimensions, length, weight, and crane usage. The resulting structured dataset is presented in Table 1. This output is formatted for direct ingestion into the computational estimation model, minimizing the need for manual data entry.

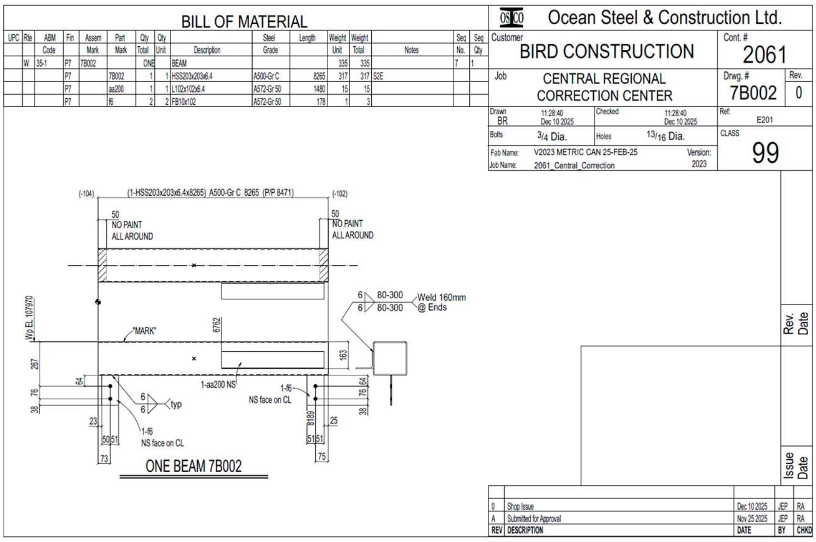

Figure 2: Selected structural steel shop drawing used in the case study.

Table 1: Structured output generated from the AI-assisted extraction of the selected shop drawing.

NUM	Con Num	Assy Mark	Part Mark	Steel Grade	Profile	Sectional Dimensions	L mm	W lbs.	crane required
1	2061	7B002	7B002	A500-Gr C	HSS	203x203x6.4	8265	317	1
2	2061	7B002	aa200	A572-Gr 50	L	102x102x6.4	1480	15	0
3	2061	7B002	f6	A572-Gr 50	FB	10x102	178	1	0
4	2061	7B002	f6	A572-Gr 50	FB	10x102	178	1	0

As shown in Table 1, beyond capturing geometric attributes, the AI-assisted method successfully inferred crane requirements from the shop drawing. This capability is critical because handling conditions such as member turning or crane-assisted lifting significantly impact overall task duration. It is worth noting that while several fields are extracted from the shop drawing, the time estimation model primarily uses profile, sectional dimensions, length, and weight to identify similar historical records. Crane usage and flip-related information is used to account for handling-related time additions.

Following data extraction, the structured attributes were subjected to a manual proof-check and then were fed into the rule-based computational model for production time estimation. The model estimates production time at the part level by identifying analogous historical records based on selected matching parameters, specifically profile, length, and weight. First, historical records with the same profile type were filtered to ensure structural equivalency. Then, at least the three closest matches are selected according to dimensional similarity (length and weight), and the average of their recorded production times was used to establish the base fitting time for each part. In addition to this similarity-based estimate, the model integrates predefined time allowances for auxiliary tasks such as reviewing and grinding. The part-level estimation results for the selected assembly are presented in Table 2, including the matched historical records, estimated time per piece, and crane usage. In Table 2, the “Similar Rows” column indicates the row numbers of historical production records selected by the rule-based model as the closest analogous cases for each extracted part. The estimated time per piece was calculated as the average observed production time of these selected records.

Table 2: Part-level estimation results obtained from the Rule-based model for the selected case

NUM	Part Mark	Profile	Sectional Dimensions	Length (mm)	W (lbs.)	Similar Rows	Estimated Time per Piece (s)	Crane Usage
1	aa200	L	102×102×6.4	1480	15	103, 96, 99	230.0	1
2	f6	FB	10×102	178	1	104, 105, 29	156.5	0
3	f6	FB	10×102	178	1	104, 105, 29	156.5	0

Table 3: Final time estimation for the assembly

Review Time (s)	Grinding Time (s)	Total Time without Crane (s)	Final Estimated Time (s)	Final Estimated Time (min)
55.8	46.8	645.6	765.6	12 min 46 sec

The final estimated production time was calculated by aggregating the baseline fitting time, additional operation-related times, and applicable crane-handling penalties. For the selected case, the final estimated production time is calculated to be 765.6 s (12 min and 46 s), while the actual observed production time was 837 s. This resulted in an absolute difference of 71.4 s, indicating that the proposed workflow underestimated the actual production time by approximately 8.5%. Given the inherent variability of manual fabrication processes, this low margin of error provides preliminary evidence of the viability of the proposed workflow to support practical, automated production time estimation in steel fabrication environments. Furthermore, the predictive fidelity of the model may improve as additional production data become available in future applications.

5 CONCLUSION

This study presented an AI-assisted, computational workflow designed to automate production time estimation in structural steel assembly by leveraging information extracted directly from static shop drawing PDFs. The proposed method combined context-aware, prompt-based extraction of assembly-related attributes with an empirically grounded estimation model supported by historical production data. By doing so, the workflow successfully bridged the persistent interoperability gap between unstructured design information and actionable production time estimation in dynamic steel fabrication environments.

The proof-of-concept application showed that the workflow can successfully extract estimation-relevant information from a selected shop drawing PDF, transform it into machine-readable, estimation-ready inputs, and use these inputs to generate a reasonable preliminary production time estimate without manual data entry. For the selected light fitting assembly, the model predicted a production time of 765.6 s, compared against an actual observed time of 837 s. Yielding a low error margin of approximately 8.5%, this result establishes a preliminary predictive baseline, particularly given the inherent behavioral and operational variability of manual fabrication tasks. Overall, the proposed method provides a transparent, scalable, and practical approach for connecting unstructured drawing information with historical shop-floor data for advanced production planning purposes.

Future work should focus on optimizing the PDF extraction stage and the estimation model by refining the extraction rules to handle higher architectural complexity and expanding the historical production dataset to capture a wider variance of fabrication conditions. Extending the method beyond light fitting assemblies to complex assembly types, multiple shop drawings, and broader scheduling applications will help evaluate the framework's generalizability. Furthermore, integrating this automated extraction pipeline with existing

Enterprise Resource Planning (ERP) systems or Building Information Modeling (BIM) ecosystems could pave the way for fully autonomous, real-time production control and dynamic scheduling in the steel construction sector.

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