



A Data-Driven Framework for Automated Generation of PC component Trailer Arrival Times: Integrating Work Interruptions Simulation and Duration Prediction

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ABSTRACT

Currently, site managers at Precast concrete (PC) construction sites are determining arrival times using simplified methods without considering duration variability and work interruptions, resulting in frequent site congestion and work delays. To address these issues, this research proposes a framework for a data-driven for automated generation of PC component trailer arrival times. By presenting multiple arrival time options according to various confidence intervals, the framework provides site managers with a flexible decision support tool that can be tailored to specific project needs. This framework will contribute to the improvement of efficiency and economic feasibility of PC construction by systematically managing the uncertainties of on-site operations. Through this framework, the limitations of existing methods that rely on experience and intuition can be overcome, and construction companies are expected to implement decision support tools optimized for their specific site characteristics using independently collected data.

KEYWORDS

Precast concrete; Trailer arrival time; Work interruption; Simulation; Duration prediction; Construction logistics

INTRODUCTION

Interest in precast concrete (PC) construction methods has been increasing due to interests in reducing the construction period, improving quality, and reducing construction waste (Wang and Hu, 2018; Tam et al. 2007). Numerous PC component trailers are delivered to PC construction sites daily, with on-site managers currently determining arrival times manually. In this manual decision-making process, there is a tendency to repeatedly designate approximate times in convenient units such as 5, 10, or 15 minutes, rather than performing precise time calculations. This uniform and simplified time allocation has limitations in adequately reflecting the complex workflow and various variables present at the construction site.

When arrival times are inappropriately determined, trailers arriving earlier than necessary increase site congestion, while late arrivals cause work interruptions due to PC component shortages (Hsu et al., 2019; Othman et al. 2017). These issues can lead to reduced work efficiency, overtime work, environmental pollution, and increases in both construction duration and costs (Liu et al. 2020;

Wu et al., 2013). To prevent these problems, a methodology for determining trailer arrival times that comprehensively considers various site conditions and constraints is necessary.

The installation time required for PC components varies depending on diverse factors such as component conditions, location conditions, installation conditions, and weather conditions, with these factors having different impacts on each work step (Jeong et al., 2024a). In actual construction sites, predictable routine interruptions (e.g., mealtimes, breaks, etc.) and unpredictable non-routine interruptions (e.g., equipment breakdowns, work interferences, etc.) occur frequently. Therefore, to determine PC component trailer arrival times, an integrated approach that systematically considers accurate time prediction along with the possibility and impact of work interruptions is essential.

To comprehensively consider these complex factors, this research proposes a framework for data-driven automated generation of PC component trailer arrival times. In this study, 'trailer arrival time' is defined as the time when a trailer arrives at the designated location for work operations. The proposed framework consists of 5 stages: (1) information loading; (2) activity list generation; (3) work interruption event generation; (4) duration prediction; (5) trailer arrival time generation. This framework will contribute to improving the efficiency and economic feasibility of PC construction by systematically managing the uncertainties of on-site operations. It has the potential to significantly reduce trailer waiting time and overtime work hours caused by work delays. Additionally, by providing data-based decision support tools to site managers, it will contribute to overcome the limitations of existing methods that rely on experience and intuition.

LITERATURE REVIEW

Research on PC component logistics management has primarily focused on transportation optimization, resource allocation, and the utilization of information systems. Jang et al. (2023) proposed a method to automate PC transportation planning through a cloud-based information system. Jang et al. (2022) developed a method to automate PC Component-Vehicle Assignment (CVA) by integrating factory, transportation, and site information. Lee et al. (2022) proposed a method to automate PC slab loading. Liu et al. (2020) proposed a dynamic optimization method for PC component transportation and storage. Despite these advances, research on trailer arrival time generation remains a significant gap in the literature. Previous studies simply used trailer arrival times manually determined by site managers based on their experience as input parameters, without developing systematic methodologies for generating these times.

Research related to work interruptions in PC construction has mostly focused on work delays rather than work interruptions. Jeong et al. (2024b) classified the causes of work interruptions into 8 flows and quantitatively calculated the probability of work interruptions occurring at each work step. Jang et al. (2024) utilized k-means clustering to quantitatively analyze work delays occurring during PC component installation. Zhao et al. (2022) evaluated the impact of risk disruption factors and developed a schedule delay prediction model based on this. Though valuable for analysis, these studies were limited in developing practical methodologies for actual construction sites.

Research on predicting the installation time of PC components has primarily been conducted using machine learning techniques. Jeong et al. (2024a) developed a duration prediction model for each work step of PC component installation using the Random Forest algorithm. Leung et al. (2001) and Tam et al. (2002) used neural networks and regression methods for hoist time prediction. However, a systematic comparison of which variable-technique combinations yield optimal predictions is lacking.

Research related to PC component simulation has typically targeted specific components. Yuan et al. (2022) simulated PC wall installation with limited interruption modeling (10% inspection failure), while Lee et al. (2015) modeled column-beam structures without directly considering interruptions. Both used triangular distributions for duration. These studies did not consider various influences, duration was considered probabilistically, and they failed to adequately model various work interruption factors.

This research complements the limitations of existing studies to reflect more realistic workflow. By deriving probabilities and duration distributions of work interruption from actual data and applying them probabilistically through simulation, work interruptions are precisely modeled. Additionally, by combining various prediction techniques to explore the optimal combination of variables and prediction techniques, the accuracy of duration prediction is improved, and based on this, a data-driven framework is proposed that automatically generates trailer arrival times.

PROPOSED FRAMEWORK FOR AUTOMATED PC TRAILER ARRIVAL TIME GENERATION

Framework overview

Figure 1 shows the proposed framework for automated generation of PC component trailer arrival times, which consists of 5 stages, each proceeding sequentially. The core of this framework is to generate trailer arrival times by combining probabilistic simulation of work interruption events and duration prediction for each work step.

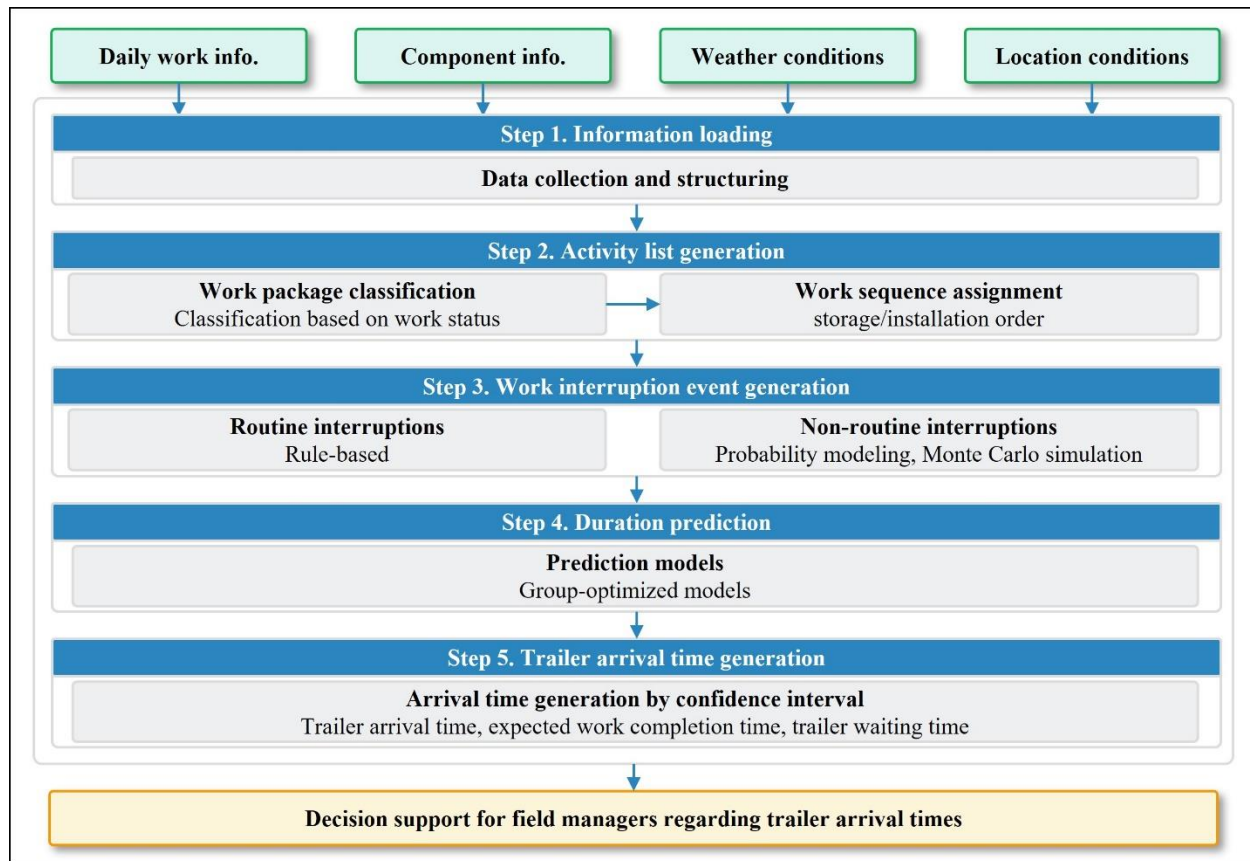


Figure 1. Framework for automated generation of PC component trailer arrival time.

Major content by stage

Step 1. Information Loading. Information loading is the stage of collecting and structuring various information needed for the day's work, and the information collected is as shown in Figure 2. This information is managed through database systems or excel files.

Identification information	Component conditions	Location conditions
- Trailer identification - Component number	- Component type - Component weight - Component area - Component length - Component height - Component variants	- Departure distance - Arrival distance - Crane angle - Location type - elevation
Work status		
- prior storage status - Same-day storage status - Same-day installation status		
Logistics info.	Weather conditions	Installation conditions
- Loading sequence - Loading position	- Temperature - Wind speed	- Lifting inserts - Fix crew size

Figure 2. Information collected in Step1.

Step 2. Activity List Generation. Activity list generation is the stage of generating a list of work steps for each PC component based on the collected information. Work package types are classified according to the working status of the components, and necessary work steps are assigned to each type (seen in Figure 3). Each activity includes information such as a unique ID, component number, work step, etc.

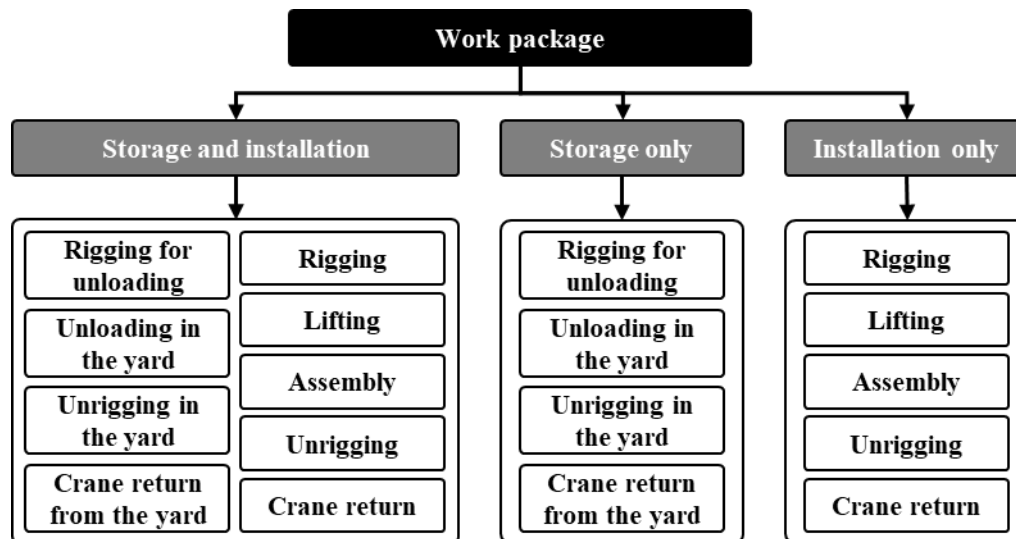


Figure 3. Work steps assigned according to work package type.

Step 3. Work Interruption Event Generation. Work interruption event generation is the stage of simulating possible work interruption events for each case in the activity list. Work interruptions are modeled as categorized in Figure 4, and various work interruption scenarios are generated through Monte Carlo simulation. Among various simulation techniques, Monte Carlo simulation

was employed because it is a computational method that relies on random sampling and probability statistics to obtain numerical results for solving probabilistic problems (Qiang, 2020).

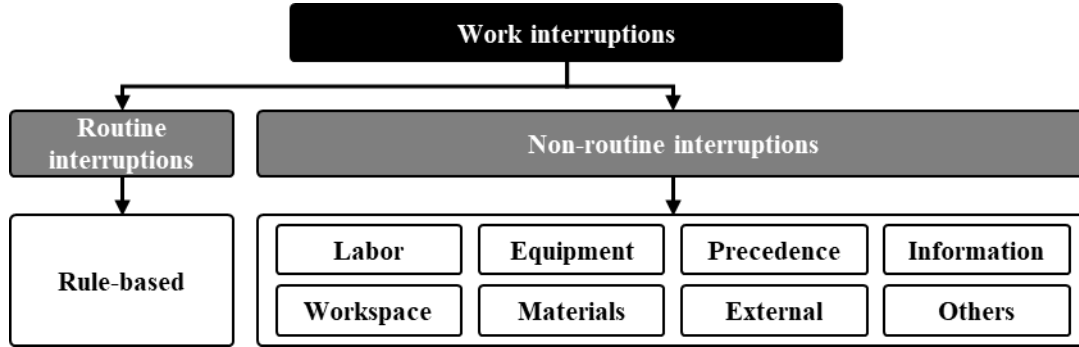


Figure 4. Classification system for work interruptions.

Step 4. Duration Prediction. Duration prediction is the stage of predicting the basic duration (i.e., pure working time without work interruptions) for each case in the activity list. The nine work steps are classified into five groups, and optimized machine learning models are applied for each group (as seen in Figure 5). The prediction models calculate duration using independent variables such as component conditions, location conditions, weather conditions, and installation conditions.

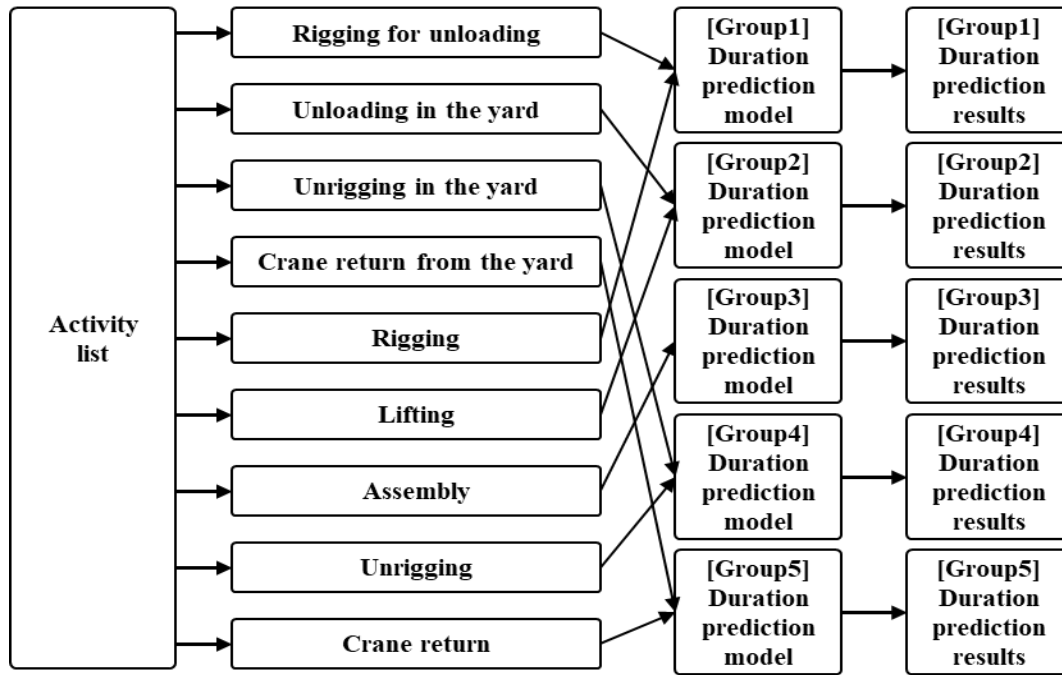


Figure 5. Process of applying duration prediction models for each work step.

Step 5. Trailer Arrival Time Generation. Trailer arrival time generation is the stage of generating trailer arrival times by integrating the results of work interruption simulation and duration prediction (as seen in Figure 6). For each confidence interval (70%, 80%, 90%, 95%), this stage determines the total duration by combining base duration and interruption time. Using the total duration, trailer arrival times are generated for each confidence interval, and based on this,

information such as expected work completion time and trailer waiting time for each scenario is provided to support the decision-making of site managers.

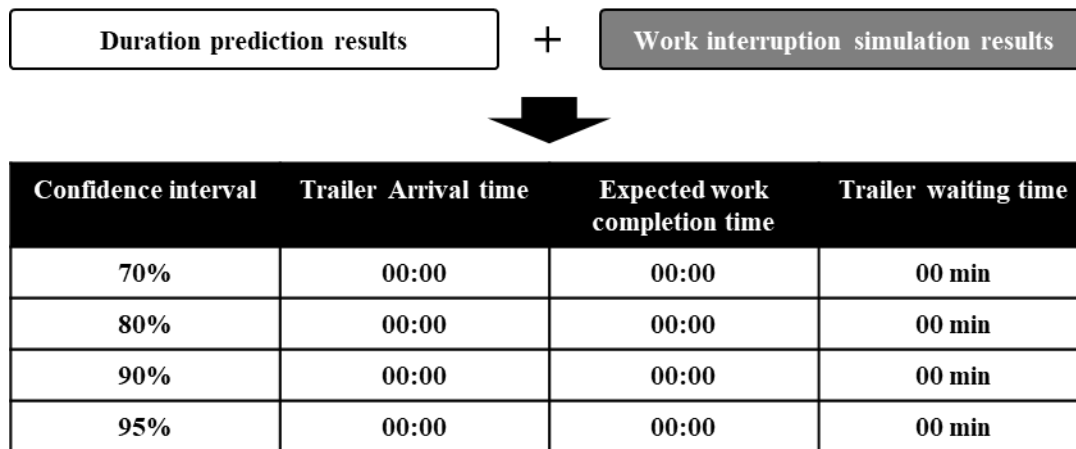


Figure 6. Structure of trailer arrival time generation model with integrated prediction results and confidence intervals.

CONCLUSION

This research proposed a data-driven framework for automated generation of PC component trailer arrival times. The proposed framework consists of 5 stages: (1) information loading; (2) activity list generation; (3) work interruption event generation; (4) duration prediction; (5) trailer arrival time generation.

The main contributions of this research are as follows:

1. Application of work interruption simulation methods utilizing distributions of actual work interruption frequencies and durations
2. Accurate duration prediction through optimal machine learning model combinations for each work step group, trained with actual duration data
3. Proposal of an arrival time generation framework integrating simulation results and prediction results
4. Development of a decision-support tool for site managers that presents arrival time options according to various confidence intervals

If construction companies build distributions of work interruption probabilities and durations, along with prediction models optimized for site characteristics by utilizing data collected from their own projects based on this framework, the efficiency of logistics management in PC construction can be greatly improved.

The framework demonstrates that effective logistics management in PC construction requires systematic consideration of onsite activity duration uncertainties. By generating arrival times that account for these uncertainties, construction managers can avoid simultaneous trailer arrivals, reduce site congestion, and minimize waiting times, significantly improving overall logistics efficiency.

In future research, verification of the framework will be conducted under diverse site conditions and component types. Additionally, the framework's performance and scope could be enhanced through the following considerations: First, the integration of external factors such as weather and traffic conditions that may affect transportation logistics; second, the exploration of site entry and movement times of trailers to designated locations; third, the expansion of the framework to

accommodate multi-crane scenarios; and finally, the improvement of both prediction model performance and the distributions of work interruption probabilities and durations through additional data collection.

In terms of practical implications, by utilizing the trailer arrival time results generated for each confidence interval, various metrics can be calculated such as trailer waiting time (the time between a trailer's arrival at the site and the commencement of work on its components), residence time (the total time a trailer remains at the construction site), and resource efficiency of equipment and labor. Site managers can refer to these calculated results and select optimal arrival times based on their management objectives (e.g., faster completion, balanced resource efficiency, reduced site congestion, etc.). This approach provides a flexible decision support tool that can be tailored to specific project needs, rather than prescribing a single correct arrival time. The implementation of this flexible decision support tool can contribute to reducing construction duration and costs in PC construction.

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