A Critical Assessment of the Support Offered by Current Construction Models for Managing Workflow in the Field

By

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ABSTRACT

Construction workflow is composed of activities and the flows necessary to execute them. Workflow variability refers to the departure from the plan in the execution of the activities and flows. Construction researchers have linked workflow variability with poor project performance and activity delays. However, there is still a need to understand the requirements for managing workflow variability in the field, and for assessing the extent to which existing construction models and methods support field managers to manage workflow variability. This paper analyzes the ability of existing construction models to represent and track workflow in the field. We found that existing models lack support for representing and tracking construction flows, and therefore cannot quantify flow variability. Moreover, our analysis of a project control data-set with over 30,000 activity entries revealed that the variables collected are poorly correlated with activity variability. Hence, current project control data cannot be leveraged to help field managers understand and manage workflow variability. To counter this limitation, we propose a theoretically based construction model that represents the construction activities and flows. We expect that the proposed construction model will enable the collection of activity and flow variability data that will help field managers to understand and manage workflow variability in the field.

KEYWORDS: construction model, workflow, workflow variability, project management

INTRODUCTION

The construction industry has recently experienced dramatic improvements in its project management tools and methods. For example, the widespread use of Building Information Modeling (BIM), lean approaches such as the use of the Last Planner System, the appearance of field information systems such, etc. However,
despite these improvements, field managers\(^1\) still face problems managing on-site construction resulting in schedule and cost overruns (Jones and Bernstein 2014).

The manufacturing industry was able to achieve exceptional performance by systematically seeking to understand and manage variability (Womack and Jones 1996). Construction researchers have also started to acknowledge the negative impact that workflow variability has on construction performance, resulting in higher work in process, longer activity durations, and project completion delays (Arashpour and Arashpour 2015). Nonetheless, field managers do not have access to methods and tools to help them manage workflow variability in the field.

This report presents our analysis of the advantages and limitations of current state-of-the-art methods available for managing workflow variability in the field. We wanted to understand to what extent the methods available allowed field managers to understand and manage workflow variability in the field. To answer this question, we carried out two research tasks. Firstly, we conducted case studies in two construction sites during an eight-week period. Secondly, we analyzed a dataset of 30,000 activities for a recently completed construction project looking for trends and indicators that could help field managers understand and predict workflow variability.

We found that projects that were implementing the Last Planner System were collecting valuable activity variability data during commitment tracking, but lacked methods for analyzing it and leveraging it for managing workflow variability. To reduce the impact of workflow variability, field managers need better methods for managing the flows between activities and for understanding how variability affects those flows. However, current methods available for managing workflow at the field level do not explicitly represent the flows between the activities. As a result, the impact of workflow variability is not measured at a level of detail that is actionable by field managers, and that can help them implement targeted measures to reduce its impact on activity execution.

Motivated by these findings, we developed a formal model of construction workflow that represents the construction activities, the flows between the activities, and the mechanisms that cause workflow variability. Using this model together with the in-project activity variance data collected through the application of the Last Planner System and the look-ahead schedule, we will formalize a method to predict the impact of workflow variability on the downstream activities and on the flows connecting the activities. We anticipate that field managers will use these predictions to implement targeted measures to reduce the impact of workflow variability on activity execution.

**MOTIVATING CASE PROBLEM**

In the first phase of the research, we were interested in understanding how field managers at construction sites managed workflow variability during the look-ahead and commitment planning. To achieve this, we carried out two case studies where we attended all the scheduling and planning related meetings during a two-month period. The first case was a seven-story office building located in South San Francisco, and the second case was a twenty-seven story office building located in downtown San Francisco.

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\(^1\) In the context of this report we apply the term field managers to those responsible for planning and controlling the work at the construction jobsite, i.e., superintendents, project engineers, and foremen.
Francisco. We found that during the look-ahead planning stage, field managers were able to intuitively identify the variability factors that could lead to variability in activity execution and formulate plans to mitigate the impact. However, facing multiple unpredicted variability factors affecting multiple related activities during short-term planning, field managers could not estimate the potential impact of workflow variability on activity execution and predict how variability would propagate to downstream activities. Hence, they could not determine whether the activities for the short-term plan could be made ready and commit to finishing them as planned.

This problem was exemplified during the planning process for the curtain wall installation activity for the seven-story office building. The field managers were concerned that the installation crew would outpace the fabrication rate for the panels. In the previous project, the installation crew suffered from frequent starvation that delayed the curtain wall installation. Since the curtain wall installation required that a six-foot workspace was left around the perimeter of the building, cascading delays occurred for other interior activities as well. For instance, there was a delay in the installation of the wall tie-ins and the construction of the raised floor.

To prevent the same situation from happening in the current project, the field managers implemented two strategies during the look-ahead planning phase: they set a ten-day material buffer to shield the installation crew from variability in the fabrication activity and created a board to actively track the progress of the curtain wall fabrication and installation activities. However, after eight days of panel production (two days before the planned start for the installation activity) the average fabrication rate was only 9.6 units/day or 20% slower than anticipated. If the fabrication rate continued at the current pace, the installation crew would run out of material on day 51 (Figure 1).

![Figure 1: Line of balance view showing the planned fabrication, planned installation, and actual fabrication for the curtain wall activity. At the current fabrication and installation rates, the installation crew will run out of material on day 51.](image)

At this point the field managers needed to make decisions to prevent the impact of the delay in the curtain wall fabrication from affecting the installation crew and the other concurrent activities. However, without a deeper understanding of the specific flows that connected the activities in the look-ahead plan, it was difficult for field managers to analyze the impact that workflow variability in the fabrication activity could have on the downstream activities. As a result, they were unable to formulate specific management actions targeted at reducing its impact.
POINTS OF DEPARTURE

The LCI defines construction workflow as the movement of information, materials, and resources (labor and equipment), through workspaces performing a sequence of activities on components (LCI 2017). Additionally, Koskela (1999) argued that workflow is enabled by seven types of flows: labor, equipment, materials and components, information, workspaces, precedence, and external. Variability is defined as “a departure from uniformity” (Hopp and Spearman 2011). Using these two definitions, we define workflow variability as a departure from the baseline (or the plan) in the execution of the flows and the activities. Variability at the flow level causes variability in the execution of the activities, leading to variability in the activity start, duration, and finish.

There are two main models that represent the construction workflow: the transformation view and the flow view. In the transformation view, the activities require a series of inputs that are transformed to create outputs. The activities are connected to each other via precedence constraints (Aalami 1998; Chapman 1997; Darwiche et al. 1988; Echeverry et al. 1991). The managerial focus is on optimizing the transformation. The transformation model does not explicitly represent the flows, which are an important workflow element. As a result, field managers cannot use the transformation model to anticipate the impact of flow variability on downstream activities or understand how variability is transmitted through the activities.

On the other hand, the flow view represents production as a series of flows composed of transformation, inspection, moving and waiting times (Koskela 2000). This view focuses on both the optimization of the flows and of the transformation (Ohno 1988). The flow view has been partially formalized into some simulation models (Akbas 2003; Choo and Tommelein 1999; González et al. 2009; Tommelein 1998), but not at the production level of detail. Hence, although the flow view represents all the workflow elements, it has not been operationalized in a construction model that can represent the workflow elements and their relationships, and measure their variability.

The Last Planner System of production control proposes to reduce workflow variability by increasing planning reliability. To increase planning reliability, only the activities that do not have any open constraints should be included in the production plan (Ballard 1999). Planning reliability is measured using the Percent Plan Complete
metric (PPC), which is calculated by dividing the number of assignments that were completed during the production horizon by the number of planned assignments over the same period (Equation 1).

\[
PPC = \frac{\text{Number of assignments completed}}{\text{Total number of planned assignments}}
\]  

(1)

PPC has been correlated with improvements in project performance (González et al. 2010) and planning reliability (Alarcón et al. 2014; Ballard 2000; Gonzalez et al. 2008). However, PPC is not a complete measure of workflow variability. A measure of activity variability requires that the activity start and activity duration are tracked. A delay in the start of the activity is normally associated to the lack of availability of an activity flow. On the other hand, a delay in the activity duration can be associated to a productivity impact or to the quality of the activity flows. The PPC only measures variability in the finish date of the activity. Therefore, PPC does not allow field managers to differentiate between factors that affect the activity start from factors that affect the activity duration. Similarly, the PPC measures the occurrence of variability in the finish date of the activity, but does not quantify the magnitude of the variability. The PPC for an activity that misses its finish date by one day is the same as the PPC for an activity that misses its finish date by four days. This prevents field managers from being able to compare the variability levels between activities. Finally, PPC serves as an indicator for workflow variability, but does not allow field managers to understand what specific activity flows were affected and to quantify their flow variability.

One of the aspects of the Last Planner System that can be most closely associated with tracking flow variability is identifying and tracking the status of the activity constraints. This process can help field managers to proactively identify and manage the flows so that they are available for the activity execution. However, there are two main limitations in the treatment of the activity constraints in the Last Planner System. Firstly, the constraints that are identified are generally external to the production system e.g., information that is required from a designer, materials that are delivered to the site, etc. However, it places less attention to internal constraints, e.g., whether two activities need the same workspace, or concurrent activities require the same equipment. Secondly, since the Last Planner System does not explicitly model the flows between the activities, it is difficult for the field managers to anticipate what the impact of variability on one flow will be on other activities that depend on the same flow. The Last Planner System does not formally track, monitor, and anticipate the impact that constraints in the make-ready process have on workflow variability (Bhargav et al. 2015). To address this limitation, we propose to formulate a model of how variability impacts construction activities, and how it is transmitted between activities.

**PROPOSED MODEL FOR ANALYZING WORKFLOW VARIABILITY**

Workflow variability occurs because of two mechanisms: the occurrence of variability factors, and the untimely release of flows from upstream activities into downstream activities.

The occurrence of variability factors can affect either the quality or quantity of the activity flows. There is a large body of literature on variability factors that affect
construction activities. Most of the contributions come from three research fields: productivity analysis (Kim et al. 2009; Korde et al. 2005; Wambeke et al. 2011), risk management risk management (Akintoye and MacLeod 1997; Chapman 1990; Dawood 1998; Levitt and Kunz 1985; Liu 2010; Tah et al. 1993), and lean construction (Alarcón et al. 2014; Ballard and Howell 1998; Choo et al. 1999; González et al. 2011; Koskela 1999; Sriprasert and Dawood 2002; Thomas et al. 2002; Tommelein et al. 1999). The most recent compilation of variability factors is from Wambeke et al. (2011). They performed an extensive literature review and cross-referenced the variability factors, reducing the list to 50 unique variability factors. Although there have been numerous studies that have attempted to quantify the impact of the variability factors on activity execution, field managers still lack a formal understanding of how these factors impact the flows between activities, and how these lead to activity variability.

The second mechanism is the untimely release of flows from an upstream activity to a downstream activity. Construction activities are interconnected by a complex network of flows. Flows released from upstream activities become inputs for downstream activities. Hence, availability of flows for downstream activities depends on the timely release of flows from upstream activities. In manufacturing, material flows between the production units are modeled using queuing models. These models give insight to managers about the impact that variability in upstream activities has on downstream activities (Hopp and Spearman 2011). In construction, the network of flows that needs to be modeled is much more complex because of the temporary nature of construction production units (Koskela 2000), yet managers do not have a method for visualizing and analyzing the flows between the activities to understand how they are interconnected. Without this knowledge, it is difficult for field managers to understand which of the flows could cause variability in activity execution and implement strategies to shield the activity from variability in that particular flow.

In the face of variability, field managers can implement buffers to shield activities from variability. There are three types of buffers: capacity, inventory, and time (González et al. 2004; Hopp and Spearman 2011). Since buffers are expensive, they should be adequately sized to match the level of variability. However, since current models do not explicitly represent and measure the flows, field managers are unable to collect data about flow variability that could help them size the buffers adequately.

Figure 1 shows our proposed conceptual model of construction workflow integrating the concepts discussed above: the flows between activities, the activities, and the mechanisms causing workflow variability (variability factors and variability in the release of flows due to activity variability).
There are theoretical gaps that need to be overcome to formalize this conceptual model into a computational representation. Firstly, we lack an understanding of what variability factors affect which flows, and how variability in the flows causes variability in the activity execution. Secondly, to operationalize the model, it is necessary to develop measures for the different components that make up the workflow model, namely, the variability factors, the variability in the flows, and the variability in the activity execution.

To start answering these questions, we wanted to have a better understanding of the importance of tracking the activity flows and the activity variability in a project that was implementing the Last Planner System. We reached out to several CIFE partners and analyzed the most complete data-set that was available to us.

**ACTIVITY TRACKING DATA-SET ANALYSIS**

The data-set was collected by a CIFE member firm. It contains the activity tracking data for a hospital project that was recently completed in California. This project implemented the Last Planner System of production control using a software tool provided by SPS. The project team held daily production planning meetings over a period of 31 months, from November 2011 to June 2014. This resulted in a record of 30,005 total activity entries. The data-set contained twenty-eight fields, such as: task name, company, planned start, planned finish, actual start, actual finish, status (completed or non-completed), category for non-completion, predecessor, and successor. We carried out a manual cleanup of the data to standardize the activity definitions (activity type, subcontractor type, and UNIFORMAT classification). Although the manual cleanup was a significantly time-intensive task (over 240 man-hours), it enabled us to group activities by different aggregations and search for trends between groups. We performed an exploratory data analysis looking for factors that could be associated with workflow variability. An interesting observation was that out of the twenty-eight fields in the data set, only one could be directly associated with the activity flows: the predecessor and successor activities. This provides evidence to the lack of support of current models for tracking variability at the flow level. Hence, we were only able to quantify workflow variability at the activity level.
A summary of the exploratory data analysis is presented in the following sections and a more extensive analysis is attached as an Appendix.

**Activity variability measures**

We calculated the activity variability measures by calculating the activity’s start, duration, and total variability.

\[ \Delta S = AS_a - PS_a \]  
\[ \Delta D = AD - PD \]  
\[ \Delta T = AF_a - PF_a \]

Where: the start variability (\( \Delta S \)) is calculated by comparing the actual start of the activity (\( AS_a \)) and the planned start of the activity (\( PS_a \)), the duration variability (\( \Delta D \)) is calculated by comparing the actual duration (\( AD \)) and the planned duration (\( PD \)) of the activity, and the total variability (\( \Delta T \)) is calculated by comparing the actual finish of the activity (\( AF_a \)) and the planned finish of the activity (\( PF_a \)).

Table 1 summarizes the activity variability measures for the activity entries in the data-set. Since the means of all the variability measures are larger than the median and the maximum values for the variables are significantly larger than the minimum, we can conclude that the distribution of the activity variability measures is skewed to the right. Hence, it is more likely for an activity to be affected by a delay than to be started or completed earlier than planned. Nevertheless, the fact that the median for all the variables is zero and the interquartile range for the variables is narrow, reveals that most of the activities are affected by variability in a small amount while a few activities are severely affected by variability.

<table>
<thead>
<tr>
<th>Variable</th>
<th>n</th>
<th>mean</th>
<th>sd</th>
<th>median</th>
<th>min</th>
<th>max</th>
<th>range</th>
<th>0.25 quant.</th>
<th>0.75 quant.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duration Var. (( \Delta D ))</td>
<td>25170</td>
<td>1.00</td>
<td>0.83</td>
<td>0.00</td>
<td>-96</td>
<td>222</td>
<td>318</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Start Var. (( \Delta S ))</td>
<td>25170</td>
<td>1.46</td>
<td>7.63</td>
<td>0.00</td>
<td>-6</td>
<td>378</td>
<td>384</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Total Var. (( \Delta T ))</td>
<td>25170</td>
<td>2.26</td>
<td>9.32</td>
<td>0.00</td>
<td>-96</td>
<td>379</td>
<td>475</td>
<td>0.00</td>
<td>2.00</td>
</tr>
</tbody>
</table>

Note – n: number of observations, sd: standard deviation, min: minimum value, max: maximum value, quant: quantile. 4,835 activities were completed without being planned and 6,209 activities did not have predecessors.

We could not establish a correlation between the start variability and the duration variability. Therefore, we found no evidence that activities that start late take longer to be completed. This observation was held after partitioning the data by subcontractor, activity type, and the different UNIFORMAT levels.

**Analysis of activity variability**

We aggregated the activity variability measures by different groupings to understand the similarities and differences in their behavior. To facilitate the analysis, we grouped the subcontractors into the following groups: Core & Shell, MEPF and Controls (MEPFC), Interior, Equipment & Furnishings (Eq. & Fur.), and Management and Supervision (Mgt).
Variability in production systems is transmitted from upstream production units to downstream production units (Hopp and Spearman 2011). As a result, generally downstream production units display higher variability. However, in the results of our analysis, upstream production units, such as Core & Shell, showed greater variability than downstream production units, such as Interior (Figure 4).

Another characteristic of production systems is that production units with reciprocal relationships tend to display higher variability than those with sequential relationships (Thomas et al. 2004). However, in our analysis we observed that activities with more sequential relationships, such as Core & Shell, displayed higher variability than activities with more reciprocal relationships, such as MEPFC (Figure 4). Similarly, 50% of the most variable activity types were Core & Shell activities (Figure 5).

Another objective of this research was to search for variables that could serve as predictors for activity variability. One of the variables that we thought could serve as a predictor was the subcontractor variable. To test this, we compared the mean total variability between the activity types executed by the same subcontractor (Figure 6). For the subcontractor variable to serve as a predictor, the activity types executed by it would need to exhibit comparable levels of activity variability. We found that there are some subcontractors whose activities exhibit a consistent level of mean total variability.
variability, such as the subcontractors for concrete, controls, fire alarm, tel/data, electrical, ceramic tile, flooring, casework, and paint. However, the activities for other subcontractors exhibit a very low consistency in the mean total variability, such as: curtain wall, exterior skin, glazing, and flashing. Subcontractors whose activities exhibit high consistency, albeit with a high mean total variability, are more predictable than subcontractors whose activities exhibit low consistency (even with a low mean total variability). Hence, the subcontractor variable is not a consistent predictor of activity variability for the current project.

![Boxplots of activity mean total variability grouped by Subcontractor type. The activity mean total variability is represented by the diamond.](image1)

**Figure 6:** Boxplots for the activity mean total variability grouped by Subcontractor type. The activity mean total variability is represented by the diamond.

![Average total variability by Sub Group](image2)

**Figure 7:** Evolution of average total variability for the activities grouped by their corresponding sub. group.

Similarly, we were interested in exploring how the total variability and the PPC for the activities behaved as the project progressed. We found that at the beginning of the project the total variability was very unstable, since there were few activities. This

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2 We do not mention the following subcontractors since they performed less than 10 different activity types: roofing, pneumatic tube, wall protection, elevator, medical equipment, mechanical engineer, management, owner, structural engineer, and seismic engineer.
behavior is analogous to a warm up period in simulation. However, after the warm up is over, the mean total variability remains relatively stable for the duration of the project (Figure 7). Tracking the average activity variability for the different activity groups could help field managers size the buffers between the activities and systematically work towards reducing the activity variability.

On the other hand, the PPC started relatively low and improved through most of the project until plateauing around 0.85 after a year and a half into the project (Figure 8). We could not establish a non-zero correlation between the activity variability and the PPC. Therefore, the PPC was not a good indicator for activity variability for this project.

Figure 9 shows the percentage of reasons for non-completion for the activities grouped by subcontractor group. It shows that the activities for the different subcontractor groups have different prevailing reasons for failing. For instance, activities that belong to the Core & Shell grouping fail about 20% of the time because of weather, whereas MEPFC activities almost never fail because of this reason. This evidence suggests that each activity type will have a certain unique pattern of reasons for non-completion. If we had information about how each of the activity flows was affected when the failure happened, we would be able to use this information to predict the impact of variability on activity execution. However, to have a certain level of certainty about the shape of the patterns we would need to collect data across several projects. It has been extremely difficult for us to get access to standardized, consistent, and detailed activity tracking because of privacy concerns and differing data collection practices between projects.
As we mentioned above, the only flow that is explicitly available in the dataset is the predecessor flow. A common assumption is that if the predecessor finishes late, the successor activity will start late. We wanted to verify this assumption by exploring the relationship between the predecessor finish variability (i.e., total variability) and the successor start variability (Figure 10). We observed that there were three clusters of activities: those whose activity start was not affected by the predecessor finishing late (orange), those whose activity start could have been affected by a predecessor finishing late (green), and those whose activity start was affected by reasons other than the predecessor finishing late (blue). There are several conclusions that can be drawn from this finding. First, that precedence constraints are not really hard constraints, successor activities can start before the predecessor finishing (note that this project carried out daily production planning and only used finish to start relationships). Second, that some activities were started late due to factors that were not modeled in the dataset. Third, that even when the predecessor finished late, the impact on the successor activity was not one-to-one.
These implications support our hypothesis that it is necessary to formally identify, measure, and track the activity flows during production planning. Only once we connect the information about flow variability with activity variability, field managers will have a fuller picture of the causes of variability and the measures they can take to shield the activities from variability. Similarly, researchers will have a higher resolution model that better reflects the reality at the jobsite, which should enable better predictive models anticipating the impact of variability and how it can be managed.

CONCLUSIONS AND FUTURE WORK

In this report, we have discussed the importance of identifying, measuring, and tracking the activity flows to help field managers manage variability during production planning. Currently, field managers do not have formal methods that help them understand or anticipate workflow variability. The most detailed activity tracking data that is currently being collected has very limited information about the activity flows and is insufficient to understand and analyze the causes and consequences of workflow variability. Moreover, it is not structured in a way that facilitates data analysis.

We have identified the need to formalize the proposed conceptual model of workflow variability into a computational representation. To achieve this, we need to overcome some theoretical and practical limitations. Firstly, we need to understand how variability in the activity flows leads to variability in the activity execution, and what variability factors affect what specific activity flows. Secondly, we need to develop measures and methods for tracking the elements that make up the workflow model, i.e., the variability factors, the activity flows, and the activity execution. A computational representation of the workflow model can help field managers understand and anticipate the impact that workflow variability has on downstream
activities as well as the project as a whole. Field managers can use this information to implement better measures to manage variability, leading to better project performance.

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APPENDIX

Start and Duration Variability Analysis for hospital data-set

Description of the data-set

The data-set contains the following fields:

- **Task_ID**: identifier for the task automatically assigned by the SPS software
- **Plan_ID**: identifier for the production plan automatically assigned by the SPS software
- **Project_BD_L1**: Level 1 of the project breakdown structure (Pre-construction or construction)
- **Project_BD_L2**: Level 2 of the project breakdown structure
- **Project_BD_L3**: Level 3 of the project breakdown structure
- **Project_BD_L4**: Level 4 of the project breakdown structure
- **Area_BD_L1**: Level 1 of the area breakdown structure
- **Area_BD_L2**: Level 2 of the breakdown structure
- **Task_Des**: Task description
- **Team**: Group of planners for the task
- **Person**: Person responsible for work
- **Discipline**: Type of work
- **Company**: Subcontractor, designer, or contractor responsible for task
- **LRM_Start**: Last responsible moment start
- **LRM_Finish**: Last responsible moment finish
- **Forecast_Start**: Date the activity is forecasted to start given the activity network
- **Forecast_Finish**: Date the activity is forecasted to finish given the activity network
- **Actual_Finish**: Date the activity was completed
Final_Status: Final status of the task i.e., completed, or completed-not-planned.
Status_Add_PP: Task status when it was added to the production plan i.e., released, released-at-risk, or blank
PP_Start: Start of the production control plan cycle
PP_End: End of the production control plan cycle
PP_Status: Task status at the end of the production plan i.e., completed, not-completed, or blank
Category_NC: category of non-completion i.e., Changed priority, Engineering information, Equipment, Failed inspection, Manpower, Material, Prerequisite, Staff not available, Underestimated, Unforeseen conditions, Weather
Root_Cause: Description of the root cause for failure
Predecessor: list of the predecessors’ Task_IDs separated by a hyphen
Successor: list of the successors’ Task_IDs separated by a hyphen
Entered_PP: date the activity was entered into SPS

The data-set was extended to include the following fields:
Activity: Standardized activity type under which the activity description falls
Subcontractor: Standardized subcontractor that would perform the activity
UNIFORMAT_L4: Uniformat level 4 classification
UNIFORMAT_L3: Uniformat level 3 classification
UNIFORMAT_L2: Uniformat level 2 classification
UNIFORMAT_L1: Uniformat level 1 classification
Unique_ID: concatenation of the Task_ID and the Plan_ID necessary to differentiate between activities that were re-entered into the production plan because they were not completed as planned

Standardizing the activity type and the subcontractor allows us to compare the analysis with other projects. Similarly, it allows us to associate the activities that are part of the same hierarchy and analyze their similarities and differences. Finally, by standardizing the activity type we can start to systematically collect information for that activity, such as its planned duration, variability, etc. This can be useful for data mining and learning in the future.

The UNIFORMAT classification groups activities by building systems, which allows us to analyze what are the similarities and differences in the variability patterns for the activities that belong to the same building system.

Activity variability measures
The hospital data-set contains a record of 30,005 activity entries. Of these, 4,835 entries were activities that were completed but were not planned. As a result, they do not have any record of the planned start or planned duration and we cannot calculate their variability measures. These activities’ variability measures are labeled as not available (NA). Activities that do not have predecessors are not affected by the predecessor finishing early or late. Therefore, the variability in the start date is
computed as the difference between the actual start and the planned start for the activity. The data-set contains 6,209 activities without predecessors.

The histograms for the variability measures reveal the long tails for the positive values of the variability measures (Figure 11). The distribution for the duration variability has both a long left-sided tail and right-sided tail, albeit a longer right-sided one. On the other hand, the distributions for the start variability caused by the activity and the start variability caused by the predecessor have a very short left-sided tail and a very long right-sided tail, revealing a high skewness. The variable start variability caused by the activity has a significantly bigger range than the variable start variability caused by the predecessor. The ranges of the variables start variability and total variability reflect the range of the variable start variability caused by the activity since they are a function of this variable.

The boxplots for the variability measures reveal similar insights. The size of the box and whiskers is very small compared to the range set by the outliers (Figure 12).
Figure 12: Boxplots for the variability measures. The box and whiskers of the boxplots are extremely tight compared to the dispersion of the outliers.

Zooming into the box and whiskers portion of the plot (Figure 13), we can see that the variables for duration variability, start variability caused by the activity, start variability caused by the predecessor, and start variability have a similar interquartile range and whiskers. This means that the bulk of the data for these variables behaves in a very similar way. However, the variable total variability has a wider range. This is expected since the variable is linear function of the start variability and the duration variability.

Figure 13: Zoom of the box and whiskers for the variability measures.
Activity variability by different groupings

In the following section, we will analyze how the activity variability varies between different activity types, subcontractors, etc.

Activity variability between different subcontractors

We grouped the subcontractors into the following groups to facilitate the analysis:

- **Core and shell:** Concrete, Curtain wall, Exterior skin, Glazing, Masonry, Misc Metals, Steel, Roofing sub
- **MEPF:** Controls, Fire Alarm, Fire Protection, Fireproofing, Mech dry, Mech wet, Plumbing, Pneumatic tube sub, Tel/Data Sub, MEPF, Electrical
- **Interior:** Ceiling, Ceramic tile, Doors & Hardware, Dry wall, Flashing sub, Flooring, Paint, Wall Protection sub
- **Equipment:** Casework, Elevator, Medical Sub, Window Shade Sub
- **Management & design:** GC, Mech Engineer, Mgt, OSHPD, Owner, Structural Eng., Seismic Engineer

Figure 14: Activity variability by activity grouping
The activities for the interior works have the greatest duration variability. The activities for the core and shell exhibit the greatest variability in the start attributable to the activity itself. On the other hand, the activities for the core and shell and the interior works have the greatest start variability caused by predecessor activities finishing late. The Core and Shell activities have the greatest total start variability. Finally, the activities for the Core and Shell and Management groupings have the greatest total variability. The activities for the Equipment and Furnishings have the smallest total variability.

Figure 15: Activity variability by activity grouping without outliers
Figure 16 shows the boxplot for the duration variability for the different subcontractors on the project. The plot reveals that the activities performed by the subcontractors with the highest duration variability are: Curtain Wall, Exterior skin, Miscellaneous Metals, Fire Protection, Fireproofing, Mechanical Dry, Mechanical Wet, Plumbing, Dry Wall, Flashing, and GC.
The activities performed by the subcontractors with the highest start variability attributable to the activity are: Curtain Wall, Exterior Skin, Glazing, Miscellaneous Metals, Dry Wall, and GC (Figure 17). There is considerable overlap between these subcontractors and those listed for the duration variability, with the exception of the MEPFC subcontractors.
Figure 18: Boxplot of start variability caused by the predecessor for the different subcontractors

The activities performed by the subcontractors with the highest start variability attributable to the predecessor are: Exterior Skin, Fireproofing, and Dry Wall.
Figure 19: Boxplot of start variability for the different subcontractors

The activities performed by the subcontractors with the highest start variability are: Curtain Wall, Exterior Skin, Glazing, Miscellaneous Metals, Dry Wall, and GC.
Overall, the activities performed by the subcontractors with the highest total variability are: Curtain Wall, Exterior Skin, Glazing, Miscellaneous Metals, Mechanical Dry, Dry Wall, Flashing, and GC. There is considerable overlap between the subcontractors that exhibit the greatest variability for the different measures.
Figure 21: Boxplot of activity total variability by different reasons for non-completion and Subcontractor groupings.

Figure 21 shows the total variability for the different activities grouped by reasons for non-completion and subcontractor groupings. The categories for non-completion that lead to the biggest total variability are: changed priority, engineering information, prerequisite, staff not available, underestimated and unforeseen conditions. Interestingly, failed inspections and weather impacts are small compared to other reasons. The activities belonging to the interiors subcontractor groupings are affected by the largest impacts.
Figure 22: Boxplot of activity total variability by different reasons for non-completion and Subcontractor groupings without outliers.

Figure 22 shows the same plot as Figure 21 without the outliers. The ranges for the total variability for the different subcontractor groupings vary within the categories for non-completion.
Figure 23 provides evidence that the activities performed by the different subcontractors have different proportions of reasons for non-completion. This information can allow us to classify activities and enable greater learning and prediction.

**Activity variability between different activity types**

Figure 24 shows the summary variables for the variability measures for all the activities with more than 10 entries. As expected, the interquantile range is very small, with the lower quantile being equal to the median. However, it is interesting to notice that for the start variability and the total variability the mean of the measures is greater than the third quantile of the distribution, signaling a strong skewness in the distribution.

<table>
<thead>
<tr>
<th>Var_Start</th>
<th>Var_Duration</th>
<th>Var_Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min. : -5.00</td>
<td>Min. : -96.00</td>
<td>Min. : -96.00</td>
</tr>
<tr>
<td>1st Qu. : 0.00</td>
<td>1st Qu. : 0.00</td>
<td>1st Qu. : 0.00</td>
</tr>
<tr>
<td>Median : 0.00</td>
<td>Median : 0.00</td>
<td>Median : 0.00</td>
</tr>
<tr>
<td>Mean : 1.459</td>
<td>Mean : 0.968</td>
<td>Mean : 2.226</td>
</tr>
<tr>
<td>3rd Qu. : 1.00</td>
<td>3rd Qu. : 1.00</td>
<td>3rd Qu. : 2.00</td>
</tr>
<tr>
<td>Max. : 378,000</td>
<td>Max. : 222,000</td>
<td>Max. : 379,000</td>
</tr>
<tr>
<td>NA's : 3,758</td>
<td>NA's : 3,758</td>
<td>NA's : 3,758</td>
</tr>
</tbody>
</table>

Figure 24: Summary variables for all the activities with more than 10 entries
Figure 25: Boxplots for the total variability for the different activity types

Figure 25 shows that the different activity types exhibit different degrees of activity variability.
Figure 26: Top 100 activities with the highest mean total variability
Figure 26 shows the top 100 activities with the highest mean total variability. Activities performed by the electrical, curtain wall, and elevator subcontractors tend to exhibit the greatest total variability.

Figure 27: Mean duration variability versus mean start variability for all the activities colored by subcontractor

There are no clear clusters of activities having similar patterns of mean start variability or mean duration variability grouped by subcontractor. This indicates that the subcontractor type might not be a good predictor for activity variability. This same pattern can be seen in Figure 28.
Figure 28: Mean duration variability versus mean start variability faceted by subcontractor group.
Similarly, Figure 29 does not reveal any clusters that can be visualized by grouping the activities by their Uniformat Level 3 classifications.