GEORGIA DOT RESEARCH PROJECT 22-22

FINAL REPORT

A SCHEDULING ASSISTANT TOOLKIT FOR GDOT'S EFFECTIVE PLANNING OF TRANSPORTATION PROJECTS



OFFICE OF PERFORMANCE-BASED MANAGEMENT AND RESEARCH

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16. Abstract

The Scheduling Assistant Toolkit was developed to enhance the Georgia Department of Transportation's (GDOT) project scheduling efficiency by providing data-driven recommendations on optimal activity overlapping strategies. Traditional scheduling methods often rely on finish-to-start dependencies, leading to unnecessarily long project durations and inefficiencies in resource utilization. This research introduces a scheduling assistant toolkit that integrates rule-based decision frameworks, risk-cost trade-off analysis, and productivity benchmarking to determine the most effective level of activity overlap while minimizing risks such as rework, inefficiencies, and delays. A key component of the study involved benchmarking location and trade productivity on a synthetic GDOT highway project to quantify productivity losses due to handoffs, work discontinuities, inefficiencies, and ineffectiveness. Results revealed that substantial productivity losses stem from crew transitions and poorly synchronized workflows, emphasizing the need for improved scheduling strategies. The toolkit utilizes Python-based algorithms to automate critical path detection, overlapping decision logic, and cost modeling, allowing project managers to evaluate various scheduling scenarios dynamically. Future developments will focus on pilot testing in GDOT projects, integration with existing scheduling systems like Primavera P6, and scalability for more complex infrastructure projects. By adopting this Scheduling Assistant Toolkit, GDOT can achieve shorter project durations, improved resource efficiency, and cost-effective construction management, setting a new standard for transportation project scheduling

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Final Report

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BOARD OF REGENTS OF THE UNIVERSITY SYSTEM OF GEORGIA BY AND ON BEHALF OF THE GEORGIA INSTITUTE OF TECHNOLOGY

Contract with Georgia Department of Transportation

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1. INTRODUCTION

In the pre-letting and pre-advertisement phase and during project definition, GDOT's Office of Construction develops an initial schedule to determine the key project milestones. The schedule is developed based on the input provided by multiple entities including utilities providers and the estimate provided by the district. However, the problem is that the schedule provided by the district includes finish-to-start relationship among activities with minimum to no overlaps. As a result, the schedules are unnecessarily long and would push the key project milestones further down the timeline. To address this issue, the State Construction Engineer of the Office of Construction noted that this office would greatly benefit from a Scheduling Assistant Toolkit that provides recommendations on the optimal level of overlapping between project activities. Furthermore, the Office of Construction would benefit from a methodology to capture true productivity rates for certain project activities (e.g., asphalt, GAB, grading/earthwork).

2. GOALS AND OBJECTIVES

This research aimed to (1) conduct literature reviews to capture the scientific approaches for identifying the optimal degree of activities overlapping, (2) find methodologies to capture true productivity rates for certain project activities (e.g., asphalt, GAB, grading/earthwork) and (3) to develop a scheduling assistant toolkit to determine the optimal degree of activities overlapping.

3. TASK REVIEW

Here are three tables summarizing the task details and expected outcomes, the current project progress, in terms of each task's status, outcomes so far, as well as the Gannt chart demonstrating the project stages.

Table 1. Task details and expected outcomes

Task Details	Expected Outcomes
<u>Task 1</u> : Conduct literature review to capture the scientific approaches	Outcome 1: Literature review results
for identifying the optimal degree of activities overlapping and	Outcome 2: Initial draft of the proposed
develop a Scheduling Assistant Toolkit for GDOT projects—an	scheduling assistant toolkit
example of these approaches is included in (Peña-Mora & Li, 2001).	
We intend to use rule-based methodologies, i.e., IF-THEN-ELSE	
constructs, to reach a conclusion for overlapping a pair of activities	
based on their attributes and risk tolerance.	
Task 2: Work with GDOT to capture true productivity rates for certain	Outcome 1: Productivity rates for
project activities (e.g., asphalt, GAB, grading/earthwork) through	certain project activities (e.g., asphalt,
benchmarking selected GDOT projects, and to identify a sustainable	GAB, grading/earthwork) on selected
set of practices for continuously capturing productivity rates in their	GDOT projects, and the list of best
future projects.	practices for continuously capturing
	productivity rates in future GDOT
	projects.

Task 3: Validate and fine-tune the Scheduling Assistant Toolkit proposed in Task 1 on a few case studies retrospectively. Conduct a charrette with GDOT personnel to show the beta-testing results and compare the proposed degree of overlap with the one suggested	Outcome 1: Beta-testing results of the Decision Assistant Toolkit on a few case studies Outcome 2: Finalized Decision
independently by a group of Subject Matter Experts (SMEs). We will	Assistant Toolkit following a charrette
evaluate the differences in results and fine-tune the Toolkit as needed.	with SMEs
<u>Task 4</u> : Develop the final research report, an interactive user guideline	Outcome 1: A draft research report
and a training video clip to enable immediate deployment of the	Outcome 2: An interactive user guide
technology in future projects. This Technology Transfer products will	Outcome 3: A training video for
expedite the Toolkit's adoption.	implementation
Task 5: Conduct a workshop with GDOT personnel to present the	Outcome 1: Final research report
research outcomes and provide training on its implementation. This	Outcome 2: Technology and knowledge
hands-on workshop will introduce the Graphical User Interface to the	transfer
Toolkit and via Use-Cases, we will show the range of uses.	

4. RESEARCH METHODOLOGY

The research methodology for this project incorporates a combination of literature review, framework development, productivity benchmarking, and tool development to ensure a systematic and data-driven approach towards optimizing activity overlap and productivity measurement in GDOT projects. This comprehensive methodology integrates both qualitative and quantitative techniques, leveraging robust computational tools and real-world data to produce actionable insights.

4.1 Literature Review and Framework Selection

The literature review part of this report seeks to consolidate existing knowledge regarding both the theoretical and practical dimensions of activity overlapping and productivity measurement in project scheduling, with a specific focus on identifying strategies which are applicable to GDOT's unique operating environment. By examining scholarly articles, case studies, and industry reports, the team identified prevailing challenges and several types of approaches in overlapping activities, particularly in transportation projects. The review section emphasized quantitative and qualitative approaches, including deterministic models, probabilistic models, optimization algorithms, and expert-judgment frameworks, to understand the trade-offs between schedule acceleration and risks such as rework and coordination failures.

Additionally, this review emphasized rule-based methodologies, especially IF-THEN-ELSE constructs which could be used to translate complex scheduling logic into more accessible, standardized decision-making processes. In this effort, this review's scope spans both foundational research and cutting-edge applications, It compasses well-established project management literature on fast-tracking, recent innovations in decision support, and field studies that illustrate how overlapping strategies have been adopted in comparable infrastructure projects.

The conclusions drawn from the review will form the basis for proposing the structure of a Scheduling Assistant Toolkit tailored to GDOT projects. This toolkit aims to encapsulate the nuanced interplay of overlapping tasks, risk tolerance, resource constraints, and productivity rate, thereby equipping GDOT with a practical yet methodological rigorous approach to accelerate project completion while minimizing adverse impacts. Building upon this foundation, the research team adopted the "Project Overlapping Decision-Making Framework," a six-step methodology for

assessing and optimizing activity overlaps (discussed in the literature review findings for task 1, Figure 2). This framework incorporates risk analysis, cost estimation, and iterative testing of overlapping scenarios, providing a structured approach to balancing schedule compression with potential penalties.

4.2 Productivity Benchmarking Framework

To address GDOT's need for accurate productivity measurement, the research utilized a framework proposed by Rathnayake et al. (2024). In this research, productivity is evaluated in two primary dimensions: *location productivity* and *trade productivity*. Location productivity evaluates inefficiencies arising from crew transitions between geographical segments of a project, quantifying the impacts of these transitions in terms of lost time or productivity. In contrast, trade productivity focuses on inefficiencies specific to individual construction trades, examining losses caused by discontinuities, idle time, and ineffective work processes. This dual-layered approach enables a comprehensive understanding of productivity challenges within GDOT's projects.

This methodology was validated using a synthetic highway project as a case study. The project included activities such as asphalt paving, graded aggregate base (GAB) installation, grading, excavation, backfilling, clearing and grubbing, and a culvert. Quantitative metrics were employed to evaluate productivity across the project. Insights from this synthetic project underscore the need for targeted strategies to optimize both location-based and trade-specific productivity, providing GDOT with actionable data to enhance project efficiency.

4.3 Scheduling Assistant Toolkit Development using Python

In developing the proposed scheduling assistant toolkit, Python programming serves as a key component of the research methodology due to its flexibility, extensive library support, and strong community backing. This toolkit aims to integrate algorithmic models for activity overlapping, along with rule-based logic, to provide recommendations to project managers. Python's broad ecosystem, encompassing libraries such as Pandas for data manipulation, NumPy for numerical operations, and SciPy for optimization, facilitates the experiment with different approaches for overlap determination, performance comparison, and method refinement based on empirical data drawn from real or simulated GDOT projects.

A central feature of the toolkit involves the application of rule-based logic, which could be conveniently implemented using Python. IF-THEN-ELSE constructs could be programmed as Python functions to handle project-specific rules, including risk thresholds, resource constraints, or phased milestones for overlapping decisions. This approach allows researchers to systematically test multiple "what-if" scenarios, adjusting activity overlap percentages or resource limitations, to gauge potential impacts on project schedules and project costs. Furthermore, Python's extensive data handling and visualization capabilities support the rigorous analysis and presentation of results derived from the scheduling toolkit. Python-based dashboards could be developed to provide project managers with interactive environment, enabling them to adjust parameters on the fly and immediately see updated scheduling scenarios. By integrating both scientific computing and user-friendly interfaces, Python reinforces the toolkit's capability to deliver actionable insights and enhance scheduling decisions for GDOT projects.

5. SCIENTIFIC APPROACHES FOR IDENTIFYING THE OPTIMAL DEGREE OF

ACTIVITIES OVERLAPPING

The literature review for Task 1 was an integral phase of the research, aimed at understanding and systematically summarizing scientific approaches for determining the optimal degree of activity overlap in construction projects. This review laid the foundation for the Scheduling Assistant Toolkit by addressing the trade-offs between schedule acceleration and the risks associated with rework. The research team explored methodologies and frameworks from academic literature and industrial practices, focusing on those that quantify the cost, risks, and duration impacts of overlapping project activities.

5.1 Activity Overlapping in Project Scheduling

Efficient scheduling is widely recognized as an important component of successful project delivery, especially in large-scale construction and infrastructure undertaken by the Georgia Department of Transportation (GDOT). Typically constrained by rigorous budgets and strict deadlines, these projects require project managers and stakeholders to seek innovative methods to reduce timelines without compromising the quality of delivery. One of the commonly adopted approaches for accelerating projects involve overlapping or fast-tracking project activities, which means executing tasks concurrently rather than in a strictly sequential manner (Salhab et al., 2023). By doing so, project teams could potentially shorten the overall schedule, optimize resource utilization, and respond more quickly to evolving project demands.

However, implementing activities overlapping in real-world projects comes with inherent challenges. For example, overlapping tasks could increase the risk of rework (Gwak et al., 2016), demand tighter coordination (Francis & Morin-Pepin, 2017), and elevate costs if coordination and communication are not managed effectively (Gwak et al., 2016). For these reasons, construction and infrastructure professionals have been interested in developing systematic, data-driven approaches to determine the optimal degree of overlap. Such methodologies not only strive to avoid pitfalls such as design errors or misaligned resource allocation but also seek to embed robust risk management protocols. As GDOT continually tackles complex and high-risk initiatives, obtaining a clear framework for fast-tracking decisions is becoming more and more essential.

Activity overlapping, often referred to as "fast-tracking", involves executing subsequent project tasks simultaneously with their predecessors, thereby reducing the overall timeline required for project delivery (Moon et al., 2015). In the context of major infrastructure projects, particularly those with significant public visibility and stakeholder involvement, overlapping has been considered as a key strategy to meet accelerating demands (Hu et al., 2015). However, the inherent concurrency of tasks introduces elevated risks, such as increased coordination complexity and the possibility of misaligned team efforts (Ibbs et al., 2007). Despite these challenges, overlapping remains a highly studied approach due to its proven capacity to shorten schedules when properly managed.

Several research suggests that overlapping decisions should be carefully aligned with the organization's risk tolerance and project governance structure (Lising & Silva, 2024; Moon et al., 2015; Rashidi Nasab et al., 2023). Robust communication systems or integrated digital platforms such as Building Information Modeling are utilized to facilitate the concurrent exchange of partial

data (Moon et al., 2015). In contrast, environments lacking frequent and transparent communication are more prone to unforeseen clashes and contract disputes. Consequently, the decision to engage in overlapping must be supported by context-specific analysis, including evaluation of interdependencies among activities, critical path determinations, and contingency plans for addressing resultant changes.

Despite these complexities, when executed strategically, overlapping could reduce idle times, optimize resource allocation, and improve stakeholder satisfaction by meeting or exceeding schedule expectations (Taghaddos et al., 2024). The challenge, therefore, lies in balancing the apparent efficiency gains against the added risks of concurrency, an issue that has propelled the development of diverse theoretical frameworks, quantitative models, and rule-based systems aiming at identifying the optimal level of overlap for each unique project scenario (Hu et al., 2015).

5.2 Recommended Degree of Activity Overlapping

The Critical Path Method (CPM) is used as a blueprint of activities occurring on the jobsite. With fast tracking becoming a norm now, a CPM schedule of activities exclusively with Finish-to-Start relationships is not considered efficient. Hence, it is important to develop CPM schedules with smart modeling relations enabling overlapping activities to better inform project implementation. If Smart Relations are to be routinely available to the planner/scheduler, then a Decision-Making Framework is needed to advise which activities qualify for overlapping and the extent of their overlap. By leveraging such a Decision-Making Framework, the planners avoid making incorrect scheduling decisions that may otherwise expose them to a higher level of risk. The end result will enable GDOT to establish a more realistic contract delivery time (Jafari et al., 2019; Jeong, 2020).

To assist GDOT with determining the optimum level of activities overlapping, the research team conducted an initial literature review. Past research has tried to support the decision-making on scheduling by finding the optimal combination of activity overlapping (Bogus et al., 2011; Gerk & Qassim, 2008; Roemer & Ahmadi, 2004). Peña-Mora & Li (2001) developed a framework to identify the maximum degree of overlapping for a pair of logically related activities on critical path based on the following three attributes: (A) evolution rate, (B) sensitivity score, and (C) reliability score. The evolution attribute reflects how the productivity rate of each activity (i.e., percent complete of an activity per unit of time) evolves until an activity is complete. The sensitivity attribute is measured by the amount of rework required in the successor activity if a change occurs in the predecessor activity. The reliability attribute reflects the accuracy and credibility of the work produced by the predecessor activity. Please see Figure 1.

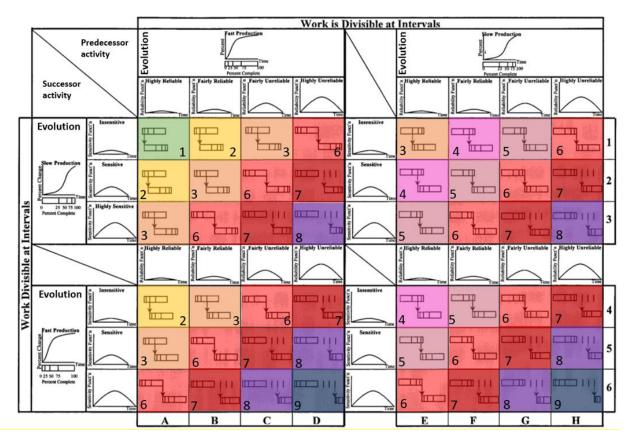


Figure 1. A Framework for determining the maximum degree of overlapping (taken from (Peña-Mora & Li, 2001))

Building upon the existing body of knowledge, this research developed a customized scheduling assistant toolkit specifically and responsive to GDOT needs.

5.3 Quantitative and Qualitative Approaches

Quantitative methods for scheduling overlap typically consists of deterministic or probabilistic models that incorporate specific cost, time, and resource variables (Dehghan et al., 2015). Deterministic models, such as linear and integer programming, allow project managers to identify optimal or near-optimal overlap levels by systematically adjusting start times, finish times, and overlap intensities (Adeli & Karim, 1997). These formulations often extend the classical critical path methods, adding overlapping as a decision variable which weights the reduction in overall duration against potential penalties, including rework costs (Dehghan et al., 2015). However, the core limitation of deterministic models lies in their assumption of stable and predictable project parameters which might not hold in rapidly changing construction environments.

In response to these limitations, probabilistic and stochastic models aim to capture the uncertainty inherent in large-scale construction projects (Dehghan et al., 2015). Monte Carlo simulation, for instance, applies random distributions to activity durations and cost metrics, generating a range of potential outcomes to quantify the probability of meeting target schedules (Rahman & Han, 2024). Bayesian updating techniques such as Bayesian Belief Network (BBN) further refines these projections by incorporating real-time data as projects progress, thereby recalibrating activity overlap recommendations based on observed performance (Luu et al., 2009). Although such methods could provide more nuanced insights into risk management for scheduling, their

successful implementation often relies on specialized expertise, significant computational capacity, and thorough data collection (M.-Y. Cheng et al., 2025).

On the qualitative side, heuristic strategies and expert-judgement models are frequently used to supplement or replace purely quantitative analysis (Moura & Scaraficci, 2008). Senior project managers, engineers, and domain experts often possess deep, context-specific knowledge that could guide overlapping decisions in ways that purely algorithmic models might overlook (Werner et al., 2017). Heuristic techniques such as Simulated Annealing and Tabu Search enable iterative discovery of near-optimal solutions, accommodating scenarios with multifaced constraints and incomplete data (Lv & Huang, 2024; Shao et al., 2024). Even though these methods lack the precision of exact optimization, they are valued for their flexibility and adaptability, particularly in projects characterized by evolving requirements and unpredictable external factors.

Combining quantitative and qualitative approaches, current researchers increasingly focus on hybrid approaches which incorporate the strengths of quantitative and qualitative methods. In practice, this might involve using a simulation-based model to generate preliminary overlap scenarios and then refining them through expert feedback sessions. By acknowledging that project environments are rarely static, and data could shift in real time, such integrative methods could ensure that overlapping decisions remain both technically sound and contextually appropriate, reducing the risk of costly missteps in large-scale infrastructure planning.

5.4 Rule-Based Methodologies for Overlapping Decisions

Rule-based methodologies transform established best practices, learned lessons, and policy requirements into a structured set of decision rules, often expressed as IF-THEN-ELSE statements (Bruno et al., 1986; Gundogar, 1999). By encoding key parameters such as risk thresholds, resource availability, and regulatory guidelines into explicit logic statements, rule-based systems provide decision-makers with clear, repeatable pathways for evaluating concurrency options. This provides a transparent framework for decision-makers, so that actions and rationale could be understood by both technical teams and oversight bodies (Gundogar, 1999).

A significant advantage of rule-based systems is their adaptability (He et al., 2022). When regulations change or new data emerges, users could adjust the relevant parameters instead of changing the entire scheduling method. This modular nature is suitable for dynamic environments, where shifting deadlines or evolving standards make it hard to maintain a rigid workflow. However, these benefits depend on regular maintenance, since outdated rules could lead to oversights or conflicts between concurrent tasks, negating the advantages of accelerated schedules. Therefore, ensuring that rules align with the latest safety, environmental, and quality requirements is of great necessity.

Integrating rule-based logic into the Scheduling Assistant Toolkit further enhances its practicality. The toolkit can serve as a user-friendly platform that consolidates data inputs, such as design completion levels, cost parameters, and staffing information, in one interface. Project managers simply enter or update these inputs, and the toolkit's inference engine, powered by the underlying rule set, offers recommendations for activity overlapping. This immediacy promotes consistency and clarity, especially when multiple stakeholders must coordinate or approve concurrency decisions. Moreover, if combined with real-time analytics, the toolkit can refine its suggestions

based on ongoing performance metrics, identifying patterns that call for a revised rule or an entirely new one.

If implemented effectively, a rule-based Scheduling Assistant Toolkit could reduce guesswork from project managers, align overlapping decisions with the project's risk appetite, and facilitate continuous improvement as the project executes. Over time, this iterative process strengthens both the toolkit's reliability and users' confidence in the system. Ultimately, rule-based methodologies offer a structured yet flexible model for managing overlapping activities, ensuring that project acceleration strategies do not come at the expense of cost control, quality, or safety.

5.5 Project Overlapping Decision-Making Framework

One of the key findings from the review was the identification of the *Project Overlapping Decision-Making Framework*, which employs a structured six-step methodology to evaluate overlapping strategies (see Figure 2).

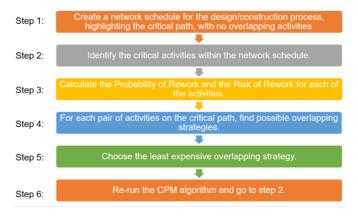


Figure 2. Six-step Project Overlapping Decision-Making Framework

This framework integrates cost, risk, duration metrics to identify the most cost-effective overlapping scenarios. A significant feature of this framework is its integration of quantitative metrics such as Cost of Rework per Day, Probability of Rework, and Indirect Cost Savings, into decision-making (see Figure 3).



Figure 3. Inputs Required for Making Overlapping Decisions

Here is an example of a synthetic project schedule consisting of eleven activities with the longest path having a duration of 27 days (see Figure 4 and Figure 5). The time-scaled fenced-bar chart and the "Critical Path Diagram" Section from the Scheduling Toolkit are displayed below, demonstrating the initial Critical Path going through activities A, B, F, H, and L (see Figure 6).

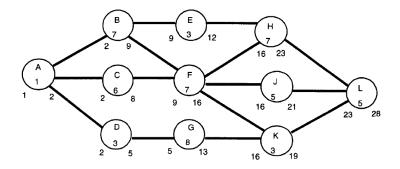


Figure 4. A Project Network Diagram used for Critical Path Method

Activity Name	Start Date	End Date	Duration	Predecessor	Successor
А	2024-01-01T00:00:00	2024-01-02T00:00:00	1		B; C; D
В	2024-01-02T00:00:00	2024-01-09T00:00:00	7	А	F
С	2024-01-02T00:00:00	2024-01-08T00:00:00	6	А	F
D	2024-01-02T00:00:00	2024-01-05T00:00:00	3	А	G
Е	2024-01-09T00:00:00	2024-01-12T00:00:00	3	В	Н
F	2024-01-09T00:00:00	2024-01-16T00:00:00	7	В; С	Н; Ј
G	2024-01-05T00:00:00	2024-01-13T00:00:00	8	D	K
Н	2024-01-16T00:00:00	2024-01-23T00:00:00	7	E; F	L
J	2024-01-16T00:00:00	2024-01-21T00:00:00	5	F	L
К	2024-01-16T00:00:00	2024-01-19T00:00:00	3	F; G	L
L	2024-01-23T00:00:00	2024-01-28T00:00:00	5	Н; Ј; К	

Figure 5. Example Schedule of the Synthetic Project

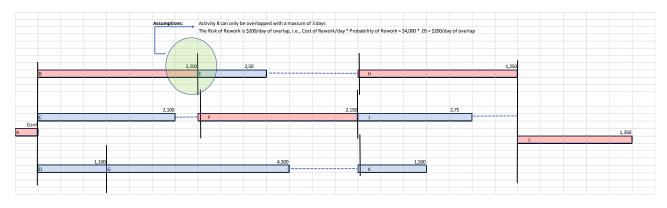


Figure 6. Time-scaled Fenced-bar Chart of the Synthetic Project

The data for Step #3 in our 6-step methodology is displayed in the figure below (see Figure 7). The overall outcome from the Project Overlapping Decision-Making Framework and the 6-step methodology will be demonstrated in the following sections.

Activity	Normal Cost	Cost of Rework/Day	Probability of Rework	Risk of Rework/Day
Α	\$3,200			
В	\$4,000	\$4,000	5%	\$200
С	\$1,200	\$2,500	4%	\$100
D	\$1,600	\$10,000	1%	\$100
Е	\$400	\$2,500	2%	\$50
F	\$2,000	\$3,000	5%	\$150
G	\$800	\$6,000	5%	\$300
Н	\$1,400	\$12,500	2%	\$250
J	\$2,800	\$3,750	2%	\$75
K	\$2,000	\$12,500	4%	\$500
L	\$1,800	\$17,500	2%	\$350

Figure 7. Cost, Probability, and Risk of Rework for Activities in the Synthetic Project

In conclusion, the Project Overlapping Decision-Making Framework bridges theoretical insights with practical applications, offering GDOT a robust tool for optimizing activity overlaps. By systematically evaluating the trade-offs between cost, risk, and schedule benefits, the framework enables data-driven decision-making which aligns with the unique challenges and constraints of GDOT's infrastructure projects. This integration of structured methodology and dynamic adaptability positions the framework as a cornerstone for an efficient project scheduling.

6. PRODUCTIVITY RATE QUANTIFICATION WITH CONSTRUCTION FLOW-

BASED METRICS

Task 2 of this research involves capturing true productivity rates for certain project activities such as asphalt paving, Graded Aggregate Base (GAB) placement, grading, and earthwork through benchmarking GDOT project activities. Additionally, a sustainable set of practices for futuristic improvements have been identified.

6.1 Construction Flow-based Productivity Quantification

This section of the review employes the framework by Rathnayake et al. (2023, 2024) and incorporate the concept of construction flow, which evaluates productivity through two key dimensions: location productivity and trade productivity. This dual-layered approach ensures a comprehensive understanding of inefficiencies stemming from both spatial constraints and tradespecific challenges, enabling actionable insights for performance optimization.

Derived from the Transformation-Flow-Value (TFV) theory of production (Koskela, 2000), Construction flow emphasizes the continuous movement of workers, materials, and equipment while identifying and eliminating non-value-adding activities such as waiting, moving, and inspecting. This flow-based perspective contrasts with the traditional transformation view, which focuses solely on converting inputs into outputs (Koskela, 2000). In construction, flow could be categorized into two primary types: (1) location or process flow, representing the flow of different

trades through a single location, and (2) trade or operation flow, representing the flow of a single trade through different locations (Sacks, 2016; Tommelein et al., 2022)(see Figure 8). While the manufacturing industry, especially the Toyota Production System (Ohno, 2019), has long embraced the flow view to improve cost-effectiveness and eliminate waste, construction has been slower to adopt these principles. This lag is partly because of the reliance on traditional tools such as Critical Path Method (CPM) and Gantt charts, which do not explicitly account for location breakdowns or process flows (Kenley & Seppänen, 2006; Olivieri et al., 2019).

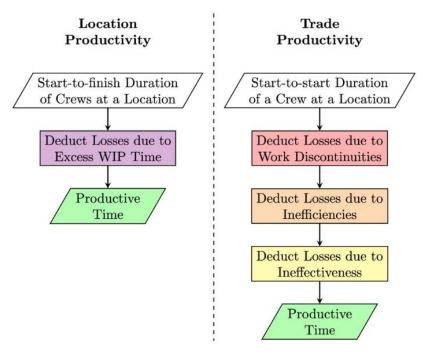


Figure 8. Framework for productivity measurement by Rathnayake et al. (2024)

Advanced planning methods, such as task-time planning, have introduced the importance of time as a parameter for improving construction flow, aligning with the recommendation from Koskela (2000) to prioritize time enhancements over cost or quality considerations.

6.2 Location Productivity

The concept of Location Productivity is targeting at understanding inefficiencies in construction projects caused by the spatial arrangement of work activities (Frandson et al., 2014). Rooted in the principles of flow management derived from manufacturing, Location Productivity focuses on evaluating the efficiency of crews operating within specific geographic segments of a project. Considered as task-time planning, this approach of measuring productivity is one the advanced techniques that predetermine crew duration for different locations. Since traditional scheduling techniques fail to account for flow inefficiencies and non-value-adding activities, modern frameworks including this location-based scheduling approach identifies productivity losses based on five metrics: (1) average batch size, (2) variability of location production rates (3) excess Work-In-Progress (WIP) time, (4) mean location production rate, and (5) overall location production rate (Rathnayake et al., 2023, 2024). Here are the explanation of these five metrics, along with the calculation formulas using the example from Rathnayake et al. (2023) (see Figure 9). In Figure 9, a_1 means the floor area of location 1, $t_{1,al}$ means the time taken to complete location 1, $t_{1,1}$, $t_{1,2}$,

and $t_{1,3}$ means the time taken to complete activities 1, 2, and 3 at location 1, $w_{1,12}$, $w_{1,23}$ means the time regrading WIP between activities 1, 2 and 2, 3 at location 1 (Rathnayake et al., 2023).

Average batch size refers to the ratio of the weighted average batch size of crews at a
location to the floor area of the location, while batch size means the average number of
unfinished locations worked on by a crew. Using the example, the average batch size could
be calculated as:

$$Average \ batch \ size = \frac{[(5+2\times4)+(4+2\times12)+1\times1]/(8+16+1)}{a_1} = \frac{1.68}{a_1} \left(\frac{1}{m^2}\right)$$

 Variability of location production rates refers to the coefficient of variation of all crew production rates in one location. High variability indicates irregular performance, leading to interruptions in flow and reduced productivity.

Variability of location production rates =
$$\frac{\sqrt{\sum_{i=1}^{3} (\frac{a_{1}}{t_{1,i}} - \frac{\overline{a_{1}}}{t_{1,i}})^{2}/3}}{(\frac{a_{1}}{t_{1,1}} + \frac{a_{1}}{t_{1,2}} + \frac{a_{1}}{t_{1,3}})/3}$$

• Excess work-in-progress time refers to the time lost during transitions between successive crews at a location. It is the ration of the total time between the start of each successive activity and the floor area of a location minus the lowest value for the entire building. Excess WIP is identified as a major contributor to productivity losses, with a strong negative correlation (r = -0.75) with overall location (Rathnayake et al., 2023). This metric emphasizes the need to minimize delays and synchronize crew handoffs.

Excess WIP time =
$$\frac{w_{1,12} + w_{1,23}}{a_1} - min(\frac{w}{a})(day/m^2)$$

• Mean location production rate refers to the average output of crews at a specific location. Higher production rates indicate greater efficiency and are positively correlated (r = 0.59) with location productivity.

Mean location production rate
$$= \frac{\frac{a_1}{t_{1,1}} + \frac{a_1}{t_{1,2}} + \frac{a_1}{t_{1,3}}}{3} (day/m^2)$$

• Overall location production rate refers to the ratio of the floor area of the location to the total duration of the location, calculated as:

Overall location production rate =
$$\frac{a_1}{t_{1,all}}(day/m^2)$$

These 5 metrics provide a comprehensive basis for evaluating location productivity and identifying the root causes of inefficiencies. Despite the advancements in flow-based scheduling, achieving optimal location productivity remains challenging due to factors such as irregular location breakdown structures and crew coordination issues. Inconsistent or oversized locations could lead

to uneven crew performance and increased congestion (Rathnayake et al., 2024), while poor synchronization among crews could lead to increase in WIP time and result in productivity losses. For example, delays in one crew's completion of work at one location can cascade to subsequent activities, causing workflow disruptions.

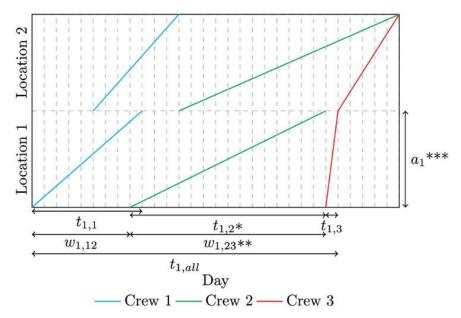


Figure 9. Calculating Process Flow Metrics Reproduced from (Rathnayake et al., 2023, 2024)

As a result, the findings on location productivity underscore the need for adopting location-based scheduling and other advanced planning techniques. It is suggested that project managers should reduce excess WIP time by optimizing handoff schedules, minimize variability in production rates through better coordination and performance monitoring, as well as leverage data-driven insights to adjust resource allocations dynamically and mitigate potential bottlenecks.

6.3 Trade Productivity

The concept of trade productivity in construction context refers to a specific trade in executing its assigned tasks across multiple locations (Sacks et al., 2017; Tommelein et al., 2022). Unlike location productivity, which focuses on spatial efficiency and crew transitions, trade productivity evaluates how effectively a single trade performs over time, considering factors such as work discontinuities, variability in production rates, and direct work efficiency. Historically, the lack of a structured approach for measuring trade productivity could lead to inefficiencies, including delays, resource underutilization, and inconsistent performance across locations.

Traditional measurement methods for productivity often rely on labor hours per unit of work completed without accounting for workflow interruptions, rework, or idling time (Seppanen & Kankainen, 2004). However, the recent focus on construction flow principles, inspired by lean production systems, has introduced more holistic approaches for analyzing trade productivity. Rathnayake et al. (2024) emphasize several key metrics for measuring trade productivity, which are level of work discontinuity, variability of trade production rates, and mean trade production rate. Here are the explanation of these three metrics, along with the calculation formulas using the example from Rathnayake et al. (2023) (see Figure 10). In Figure 10, a_1 , a_2 , a_3 , a_4 means the

floor area of location 1, 2, 3, and 4, $t_{all,1}$ means the time taken for crew 1 to complete in four locations, $t_{1,1}$, $t_{2,1}$, $t_{3,1}$, and $t_{4,1}$ means the time taken to complete location 1, 2, 3, and 4 by crew 1 (Rathnayake et al., 2023).

• Level of work discontinuity refers to the ratio of total non-working time between locations to the total area. It measures the productivity losses due to idle time when a crew is not actively working at a location. The study found a strong negative correlation (r = -0.72) between work discontinuity and trade productivity, indicating that reducing idle time is crucial for improving efficiency (Rathnayake et al., 2023).

Level of work discontinuity =
$$\frac{d_{12,1} + d_{23,1} + d_{34,1}}{a_1 + a_2 + a_3 + a_4} (day/m^2)$$

• Variability in trade production rates refers to the inconsistencies in performance across different locations. High variability suggests poor coordination and fluctuating productivity, potentially leading to inefficient scheduling. While this metric demonstrates a weaker correlation with overall trade productivity, its impact is still significant when combined with work discontinuity.

$$Variability\ in\ trade\ production\ rates = \frac{\sqrt{\sum_{i=1}^{4}(\frac{a_i}{t_{i,1}} - \overline{\frac{a_i}{t_{i,1}}})^2/4}}{(\frac{a_1}{t_{1,1}} + \frac{a_2}{t_{2,1}} + \frac{a_3}{t_{3,1}} + \frac{a_4}{t_{4,1}})/4}$$

• Mean trade production rate refers to the average production rate of a crew across multiple locations. A higher mean trade production rate is associated with improved workflow efficiency, but it must be evaluated alongside work discontinuity to provide a complete picture of trade performance.

Mean trade production rate =
$$\frac{a_1 + a_2 + a_3 + a_4}{t_{all.1}} (m^2/day)$$

The integration of these three metrics provides a data-driven approach to identifying inefficiencies and improving scheduling reliability. However, several challenges persist in optimizing trade productivity. One of them is regarding work discontinuities, which occurs when trades experience prolonged idle periods due to sequencing issues, lack of preparatory work, or scheduling misalignment. Rathnayake et al. (2024) found that approximately 52% of total time due to work discontinuities could be lost for trade crews, significantly impacting their overall productivity. Moreover, unlike controlled manufacturing environments, construction sites often face unpredictable delays including weather disturbances, material shortages, and sequencing errors. High variability in production rates could lead to inefficient crew deployments, further reducing trade efficiency.

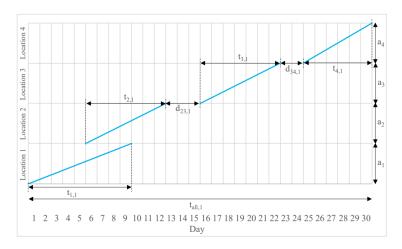


Figure 10. Calculating Operations Flow Metrics Reproduced from (Rathnayake et al., 2023, 2024)

Consequently, as for insights from the trade productivity framework, proactive scheduling strategies and real-time monitoring is suggested to reduce inefficiencies. Minimizing work discontinuity through optimized sequencing could significantly reduce idle time and improve overall trade efficiency. Using IoT-enabled devices and construction management software could enable real-time monitoring of trade performance, assisting project managers in adjusting schedules dynamically. Establishing benchmarks for trade production rates could also facilitate comparative performance analysis across projects.

7. CAPTURE TRUE PRODUCTIVITY RATES THROUGH BENCHMARKING A SYNTHETIC GDOT PROJECT

The purpose of this section is to present a comprehensive analysis of trades productivity by capturing true productivity rates for key project activities within the synthetic GDOT project framework. This benchmarking process considers both the location productivity, represented by the losses incurred during crew handoffs, and trade productivity, represented by the losses associated with work discontinuities, inefficiencies, and ineffectiveness. By doing so, the framework provides a granular view of productivity challenges and offers actionable insights for future project planning and resource allocation.

The Synthetic Highway Project, designed for benchmarking purposes, is structured with 100 stations, divided into two sections. Section #1 spans Stations 50-100, while Section #2 spans Stations 0-50. The project integrates multiple trade activities including Clearing and Grubbing, Graded Aggregate Base (GAB), Paving, Excavation, Backfilling, Grading, and Culvert installation. Details include Cut A between Stations 10-30, Cut B between Stations 50-60, Grading between Stations 60-70, Backfilling between Stations 30-50, a Culvert at Station 40, Clearing and Grubbing between Stations 0-100, GAB between Stations 0-100, and Paving between Stations 0-100. Additionally, this project schedule incorporated real-world constraints commonly faced by GDOT, such as site restrictions between Stations 40-100 during the first two weeks of September and a winter shutdown beginning in mid-December. The project's NTP is September 1st, and the Project Completion date is the 2nd week in December. This controlled yet realistic project setup

is ideal for capturing true productivity rates by isolating the effects of various operational challenges (see Figure 11).

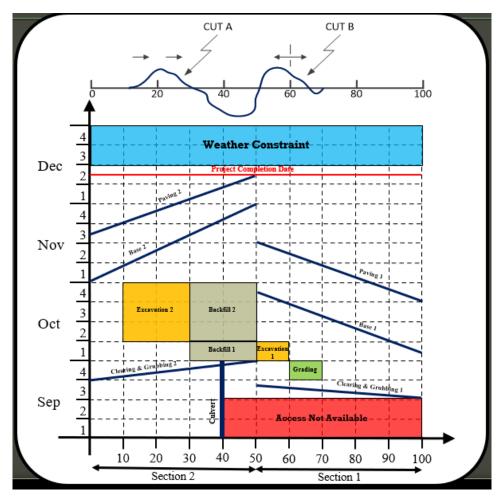


Figure 11. Project Schedule of a Synthetic Highway Project for GDOT

7.1 Quantification of Location Productivity – Losses Due to Handoffs

One of the primary productivity losses in construction projects stems from handoffs between crews. These losses occur when work progresses from one team to another, leading to delays in continuity and efficiency. Here is a table displaying the actual start-to-start duration in weeks for the two sections (see Table 2 and Figure 12). The calculations for excess work in progress and the resulting handoffs are summarized as follows.

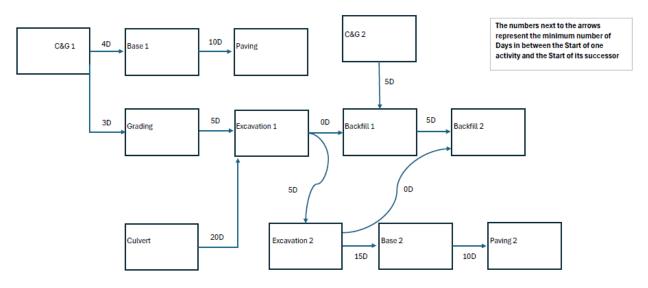


Figure 12. Logical relationships among activities for the Synthetic GDOT Project

Table 2. Duration of each activities for the Synthetic GDOT project

Section	Clearing & Grubbing I to Base I	Base 1 to Paving 1	Grading to Excavation I	Clearing & Grubbing I to Grading	Culvert to Excavation 1	Excavation 1 to Backfill 1	Clearing & Grubbing 2 to Backfill 1	Backfill I & Backfill 2	Excavation 2 to Backfill 2	Excavation 2 to Base 2	Base 2 to Paving 2	Excavation 1 to Excavation 2
Section #1	13	13	5	5	20	0	N/A	N/A	N/A	N/A	N/A	N/A
Section #2	N/A	N/A	N/A	N/A	N/A	N/A	5	5	0	15	13	5

• Section 1:

Total Excess Work In Progress
$$= [(13-4) + (13-10) + (5-5) + (5-3) + (20-20) + (0-0)] = 14$$
Average Proportion of Loss = $\frac{14}{40}$ = 35%

• Section 2:

Total Excess Work In Progress
$$= (5-5) + (5-5) + (0-0) + (15-10) + (13-10) + (5-5) = 8$$

$$Average \ Proportion \ of \ Loss = \frac{8}{53} = 15.1\%$$

• Overall Project:

Combined Handoff Losses =
$$\frac{14+8}{40+53}$$
 = 23.7%

Here is also a diagram visually representing the excess work in progress caused by handoffs between different construction phases for Section 1 (represented by blue solid line) and Section 2 (represented by green dashed line). The x axis lists the different transitions between construction activities, while the y-axis quantifies the excess work in progress in days (see Figure 13).

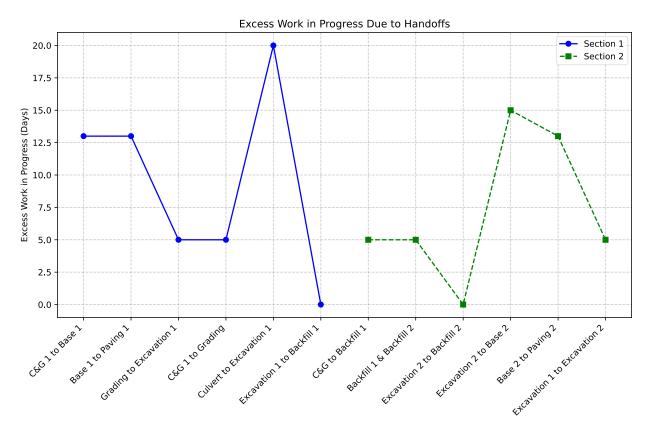


Figure 13. Excess Work in Progress Due to Handoffs in the Synthetic Project

From this diagram, in terms of Section 1, we could find out that the largest WIP delays are observed at *Culvert to Excavation 1* (20 days), including substantial inefficiencies. Minimal delays occur for *Grading to Excavation 1* (5 days) and *Clearing & Grubbing 1 to Grading* (5 days). *Excavation 1 to Backfill 1* shows 0 days, indicating smooth transition at this stage. In terms of Section 2, the largest delays are observed at *Excavation 2 to Base 2* (15 days), emphasizing a significant handoff issue. A noticeable delay of 13 days occurs at *Base 2 to Paving 2*, indicating potential scheduling or resource allocation challenges. Other transitions, such as *Backfill 1 to Backfill 2* (5 days) and *Excavation 2 to Backfill 2* (0 days), indicate smoother transitions compared to Section 1.

These findings indicate that Section 1 experiences significantly higher losses due to handoffs compared to Section 2, emphasizing the need for better scheduling, resource allocation, and crew coordination.

7.2 Quantification of Trade Productivity – Losses Due to Work Discontinuities

Work discontinuities occur when there are gaps in activity between different sections of the project, affecting overall productivity. This formula is used to calculate these losses:

$$Percentage \ of \ Loss = \frac{Days \ without \ installation \ (Discontinuity)}{Total \ days \ (Finish-Start)}$$

Applying this formula to the synthetic project, based on Figure 11, the results for key trades are:

Clearing and Grubbing

Since the start of Section 1 is at week 2.00, the finish of Section 1 is at week 2.75, the start of Section 2 is at week 3.00, the finish of Section 2 is at week 4, then

$$Discontinuity = 3.00 - 2.75 = 0.25 weeks$$

Hence, the percentage of loss for each section is:

Percentage of Loss for Section 1 =
$$\frac{0.25}{(2.75 - 2.00) + 0.25} = 25\%$$
Percentage of Loss for Section 2 =
$$\frac{0}{(3.00 - 2.00) + 0} = 0\%$$

Base Preparation

Since the start of Section 1 is at week 4.50, the finish of Section 1 is at week 7.50, the start of Section 2 is at week 8.00, the finish of Section 2 is at week 12.00, then

$$Discontinuity = 8.00 - 7.50 = 0.5$$
 weeks

Hence, the percentage of loss for each section is:

Percentage of Loss for Section 1 =
$$\frac{0.5}{(7.50 - 4.50) + 0.25} = 14\%$$
Percentage of Loss for Section 2 =
$$\frac{0}{(12.00 - 8.00) + 0} = 0\%$$

Paving

Since the start of Section 1 is at week 7.00, the finish of Section 1 is at week 10.00, the start of Section 2 is at week 10.50, the finish of Section 2 is at week 13.50, then

$$Discontinuity = 10.50 - 10.00 = 0.5 weeks$$

Hence, the percentage of loss for each section is:

Percentage of Loss for Section 1 =
$$\frac{0.5}{(10.00 - 7.00) + 0.5} = 14\%$$
Percentage of Loss for Section 2 =
$$\frac{0}{(13.50 - 10.50) + 0} = 0\%$$

Excavation

Since the start of Section 1 is at week 4.00, the finish of Section 1 is at week 5.00, the start of Section 2 is at week 5.00, the finish of Section 2 is at week 8.00, then

$$Discontinuity = 5.00 - 5.00 = 0$$
 weeks

Hence, the percentage of loss for each section is:

Percentage of Loss for Section 1 =
$$\frac{0}{(5.00 - 4.00) + 0}$$
 = 0%

Percentage of Loss for Section 2 =
$$\frac{0}{(8.00 - 5.00) + 0}$$
 = 0%

Backfill

Since the start of Section 1 is at week 4.00, the finish of Section 1 is at week 5.00, the start of Section 2 is at week 5.00, the finish of Section 2 is at week 8.00, then

$$Discontinuity = 5.00 - 5.00 = 0$$
 weeks

Hence, the percentage of loss for each section is:

Percentage of Loss for Section 1 =
$$\frac{0}{(5.00-4.00)+0}$$
 = 0%

Percentage of Loss for Section 2 =
$$\frac{0}{(8.00-5.00)+0}$$
 = 0%

Consequently, these calculations conclude that discontinuities are primarily concentrated in Section 1, contributing to inefficiencies in the project timeline.

7.3 Quantification of Trade Productivity – Losses Due to Work Inefficiencies

Work inefficiencies arise when crews experience excessive idle time or engage in indirect work. This can be measured using the formula:

$$Percentage \ of \ Loss = \frac{\textit{Days without direct work}}{\textit{Total days (Finish-Start)}} = \frac{\textit{Continued work days} \times (1 - \textit{direct work\%})}{\textit{Continued work days+discontinuity}}$$

Applying this formula to the synthetic project, based on Figure 11, the results for key trades are:

Clearing and Grubbing

Since the discontinuity is 0.25 weeks, assume the percentage of direct work is 60%, then the percentage of loss for each section is:

Percentage of Loss for Section 1 =
$$\frac{(2.75 - 2.00) \times (1 - 60\%)}{(2.75 - 2.00) + 0.25} = 30\%$$

Percentage of Loss for Section 2 =
$$\frac{(3.00 - 2.00) \times (1 - 60\%)}{(3.00 - 2.00) + 0} = 40\%$$

Base Preparation

Since the discontinuity is 0.5 weeks, assume the percentage of direct work is 55%, then the percentage of loss for each section is:

Percentage of Loss for Section 1 =
$$\frac{(7.50 - 4.50) \times (1 - 55\%)}{(7.50 - 4.50) + 0.5} = 39\%$$

Percentage of Loss for Section 2 =
$$\frac{(12.00 - 8.00) \times (1 - 55\%)}{(12.00 - 8.00) + 0} = 45\%$$

Paving

Since the discontinuity is 0.5 weeks, assume the percentage of direct work is 80%, then the percentage of loss for each section is:

Percentage of Loss for Section 1 =
$$\frac{(10.00 - 7.00) \times (1 - 80\%)}{(10.00 - 7.00) + 0.5} = 17\%$$

Percentage of Loss for Section 2 =
$$\frac{(13.50 - 10.50) \times (1 - 80\%)}{(13.50 - 10.50) + 0} = 20\%$$

Excavation

Since the discontinuity is 0 weeks, assume the percentage of direct work is 45%, then the percentage of loss for each section is:

Percentage of Loss for Section 1 =
$$\frac{(5.00 - 4.00) \times (1 - 45\%)}{(5.00 - 4.00) + 0} = 55\%$$

Percentage of Loss for Section 2 =
$$\frac{(8.00 - 5.00) \times (1 - 45\%)}{(8.00 - 5.00) + 0} = 55\%$$

Backfill

Since the discontinuity is 0 weeks, assume the percentage of direct work is 45%, then the percentage of loss for each section is:

Hence, the percentage of loss for each section is:

Percentage of Loss for Section 1 =
$$\frac{(5.00 - 4.00) \times (1 - 45\%)}{(5.00 - 4.00) + 0} = 55\%$$

Percentage of Loss for Section 2 =
$$\frac{(8.00 - 5.00) \times (1 - 45\%)}{(8.00 - 5.00) + 0} = 55\%$$

Consequently, these calculations conclude that excavation and backfill activities suffer the highest inefficiencies, potentially due to poor coordination or equipment availability.

7.4 Quantification of Trade Productivity – Losses Due to Work Ineffectiveness

Work inefficiencies arise when crews experience excessive idle time or engage in indirect work. This can be measured using the formula:

$$Percentage \ of \ Loss = \frac{\textit{Time lost from slower pace}}{\textit{Total days (Finish-Start)}} = \frac{\textit{Direct work days} - \frac{\textit{Number of Stations}}{\textit{Work Effectiveness}}}{\textit{Continued work days+discontinuity}}$$

Applying this formula to the synthetic project, based on Figure 11, the results for key trades are:

Clearing and Grubbing

Since the discontinuity is 0.25 weeks, assume the percentage of direct work is 60%, then

Direct work days for Section
$$1 = (2.75 - 2.00) \times 60\% = 0.45$$
 weeks
Direct work days for Section $2 = (3.00 - 2.00) \times 60\% = 0.6$ weeks

Work Effectiveness =
$$Max(\frac{Number\ of\ Stations\ or\ Covered\ Volume}{Direct\ work\ days}) = \frac{50}{0.45}$$

= 111.11(Stations/week)

Percentage of Loss for Section 1 =
$$\frac{0.45 - \frac{50}{111.11}}{(2.75 - 2.00) + 0.25} = 0\%$$

Percentage of Loss for Section 2 =
$$\frac{0.6 - \frac{50}{111.11}}{(3.00 - 2.00) + 0} = 15\%$$

Base Preparation

Since the discontinuity is 0.5 weeks, assume the percentage of direct work is 55%, then

Direct work days for Section
$$1 = (7.50 - 4.50) \times 55\% = 1.65$$
 weeks

Direct work days for Section 2 =
$$(12.00 - 8.00) \times 55\% = 2.2$$
 weeks

Work Effectiveness =
$$Max(\frac{Number\ of\ Stations\ or\ Covered\ Volume}{Direct\ work\ days}) = \frac{50}{1.65}$$

= 30.3(Stations/week)

Percentage of Loss for Section 1 =
$$\frac{1.65 - \frac{50}{30.3}}{(7.50 - 4.50) + 0.5} = 0\%$$

Percentage of Loss for Section 2 =
$$\frac{2.2 - \frac{50}{30.3}}{(12.00 - 8.00) + 0} = 14\%$$

Paving

Percentage of Loss for Section
$$1 = \frac{2.4 - \frac{50}{20.83}}{(10.00 - 7.00) + 0.5} = 0\%$$

Percentage of Loss for Section 2 =
$$\frac{2.4 - \frac{50}{20.83}}{(13.50 - 10.50) + 0} = 0\%$$

Excavation

Backfill

Since the discontinuity is 0 weeks, assume the percentage of direct work is 45%, then

Direct work days for Section 1 =
$$(5.00 - 4.00) \times 45\% = 0.45$$
 weeks

Direct work days for Section 2 = $(8.00 - 5.00) \times 45\% = 1.35$ weeks

Work Effectiveness = $Max(\frac{Number\ of\ Stations\ or\ Covered\ Volume\ Direct\ work\ days}{0.45, \frac{5000}{0.45}, \frac{20,250}{1.35}}) = 15,000(Cubic\ Yard/week)$

Percentage of Loss for Section 1 = $\frac{0.45 - \frac{5000}{15,000}}{(5.00 - 4.00) + 0} = 12\%$

Percentage of Loss for Section 2 = $\frac{1.35 - \frac{20,250}{15,000}}{(8.00 - 5.00) + 0} = 0\%$

Consequently, these calculations demonstrate that Section 2 generally operates at a slower pace than Section 1, particularly in the *Clearing & Grubbing*, and *Base Preparation*.

7.5 Summary of Quantification of Location and Trade Productivity

This benchmarking analysis of the Synthetic GDOT Project provides a structured approach to assessing productivity rates by quantifying losses due to handoffs among crews and trade-specific inefficiencies. Here is a bar chart demonstrating all the calculation results (see Figure 14). Through a detailed breakdown of discontinuities, inefficiencies, and ineffectiveness across various project activities, we could identify key areas for improvement and optimization in future highway construction projects.

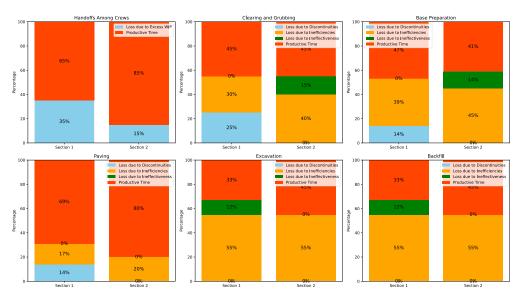


Figure 14. Detailed Calculation Results for Location and Trade Productivity Losses of the Synthetic GDOT Project

Handoffs Among Crews: A Major Productivity Constraint

The handoffs among crews resulted in substantial productivity losses, particularly in Section 1, which experienced a 35% loss due to excess Work In Progress (WIP), compared to only 15.1% in Section 2. This suggests that Section 1 suffered from inefficient task transitions, delays between crews, or misalignment in scheduling, significantly impacting workflow continuity. Overall, handoff-related productivity losses accounted for 23.7% of the total project duration, emphasizing the need for better crew coordination and work sequence.

Trade Productivity: Identifying Key Ares of Inefficiency

The results for the trade-specific productivity rates reveals considerable variations between Section 1 and Section 2 across different activities, as outlined by activities below:

- Clearing and Grubbing: Section 1 suffered a 25% loss due to discontinuities, while Section 2 had no such losses. Inefficiencies were higher in Section 2 (40%) compared to Section 1 (30%), suggesting workflow delays or excessive idle time. Overall productive time remained at 45% for both sections.
- *Base Preparation*: Section 1 recorded 14% loss due to discontinuities, whereas Section 2 had none. Inefficiencies were higher in Section 2 (45%) compared to Section 1 (39%), indicating delays in material or equipment availability. Productive time in Section 2 (41%) was lower than in Section 1 (47%), highlighting scheduling misalignments.
- *Paving*: Losses due to discontinuities were 14% in Section 1 and 0% in Section 2, suggesting a smoother execution in the latter. Inefficiencies were slightly higher in Section 2 (20%) compared to Section 1 (17%). Productive time was higher in Section 2 (80%) compared to Section 1 (69%), making it the most efficient activity.
- *Excavation*: Section 1 experienced 12% loss due to discontinuities, while Section 2 had none. Both sections suffered from high inefficiencies (55%), likely due to equipment downtime or poor task sequence. Work pace issues contributed to 12% additional loss in Section 1, but Section 2 avoided this issue. Productive time was significantly lower in Section 1 (21%) than in Section 2 (45%), indicating severe bottlenecks in Section 1.
- *Backfill*: Section 1 experienced 12% loss due to discontinuities, whereas Section 2 had none. Both sections faced high inefficiencies (55%), indicating excessive idle time or resource misallocation. Work pace losses were observed only in Section 1 (12%). Productive time was lower in Section 1 (21%) compared to Section 2 (45%), reflecting overall inefficiencies in material placement and compaction.

Recommendations Based on the Results

First of all, it's recommended that better crew scheduling and task coordination should be taken into account. The higher handoff losses in Section 1 (35%) suggest a need for tighter sequencing of crews and reducing idle time between work phases. Secondly, *Excavation* and *Backfill* processes should be optimized since these activities recorded the highest inefficiencies (55%), indicating opportunities for better resource allocation and equipment utilization. Finally, it's better to leverage productivity gains in Section 2 because *Paving* in Section 2 had the highest productive time (80%), demonstrating a more optimized workflow that could be replicated across other trades.

8. OTHER PRACTICES FOR PRODUCTIVITY MEASUREMENT

Besides productivity rate quantification through construction flow-based methods, other practices have also been identified to address inefficiencies in GDOT projects while fostering a culture of continuous improvement. The integration of *Standardized Operating Procedures*, *Benchmarking with Historical Data for Performance Optimization*, and *Granular Activity Tracking for Task-Level Optimization* enhances productivity measurement accuracy and ensures long-term sustainability in GDOT projects.

8.1 Standardized Operating Procedures

Standardized Operating Procedures (SOPs) are critical for maintaining uniformity, accuracy, and efficiency in productivity measuring and tracking across construction projects. According to Vigneshwar & Shanmugapriya (2024), increasing construction productivity is complicated due to the interconnected characteristics and absence of a standardized approach for measuring different types of activities. Therefore, SOPs should be established for key productivity measurement processes, including data collection, reporting frequency, and validation methods. Clear roles and responsibilities should be defined for project managers, filed supervisors, and data analysts to ensure accurate productivity assessments. In response to this need, Vigneshwar & Shanmugapriya (2024) proposes a theoretical Productivity Measurement Model (PMM) to address the challenges associated with productivity assessment from three levels: Operational Efficiencies (OE), Management/Administration Efficiencies (ME), and Industry/Sector Efficiencies (IE). Saggin et al. (2017) present the results of increased productivity through standardization of work and their application on a construction site. Gurmu et al. (2016) also suggests that the productivity of management practices should be measured by using validated standard questionnaires. These papers promote the adoption of SOPs to ensure the productivity quantification remain consistent and replicable, eliminating discrepancies caused by subjective observations or inconsistent reporting practices.

In addition, standardization efforts should be accompanied by digital documentation (Kovachev et al., 2014) and automation tools such as Procore, Autodesk BIM 360, and Oracle Primavera to ensure that SOPs are seamlessly integrated into day-to-day operations. Mobile applications empower filed teams to log data instantly, enhancing the accuracy and timeliness of productivity tracking while enabling seamless synchronization of productivity data along with schedules and cost estimations (Ratajczak et al., 2017). Digital checklists and automated alerts within these applications could enforce compliance with productivity tracking procedures, ensuring critical data points are captured in real-time. The emergence of Building Information Modeling (BIM) as a transformative tool in construction management has also allowed for dynamic comparison of planned versus actual productivity within a standardized platform.

Ensuring effective implementation of SOPs requires ongoing training for project personnel. These training programs should equip stakeholders with necessary skills regarding standardized data entry formats, productivity benchmarks, and data verification methods to enhance the reliability of productivity reporting (Hashim et al., 2024). By incorporating SOPs into the GDOT Scheduling Assistant Toolkit, construction managers could standardize productivity tracking process across projects, leading to greater transparency and improved decision-making.

8.2 Benchmarking with Historical Data for Performance Optimization

Benchmarking with historical data allows GDOT to establish realistic performance expectations and optimize construction schedules based on prior project insights. Through analysis of past productivity trends, managers could identify patterns of inefficiencies and best practices, leading to data-driven scheduling decisions.

Three specific actions could be taken: (1) establishing productivity baselines, (2) continuous benchmark updates, and (3) comparative performance analysis. First of all, GDOT could leverage historical data from completed infrastructure projects, such as lane-miles paved, cubic yards of earthwork completed, and bridge construction timelines, to set performance benchmarks. Additionally, based on the research by (Borcherding et al., 1980; Borcherding & Garner, 1981), nine major factors could influence project productivity, which are material availability, tool availability, rework, overcrowded work area, inspection delays, supervisor incompetence, crew interfacing, craft turnover and absenteeism, and supervisor changes. Since most of these factors are considered universal, productivity baselines could be developed based on these factors.

Since benchmarking is a dynamic process, productivity baselines should also be regularly updated according to the workforce productivity trends, technological advancements, and material cost fluctuations. Several studies have tried to investigate the causes and implications of workforce productivity trends (Allmon et al., 2000; Gong et al., 2011; Goodrum et al., 2002; Goodrum & Haas, 2004; Rojas & Aramvareekul, 2003). According to the study by Allmon et al. (2000), workforce productivity trends are influenced mainly by six factors: project uniqueness, technology, management, labor organization, real wage trends, and construction training. What's more, the study by Sanvido (1988) provides a categorization of four management practices to improve labor productivity, including planning, resource supply and control, supply of information and feedback, and selection of the right people to control certain factors. Referring to these factors identified by literature, benchmarking could remain accurate and relevant across different project scopes. When performance of a project falls below established benchmarks, GDOT could make proactive adjustments by reallocating resources or revising project timelines, preventing delays and minimizing budget overruns.

Lastly, as for comparative performance analysis, projects with similar scales, location, and environmental conditions could be grouped together and analyzed to identify productivity trends and process inefficiencies. A study by Winch & Carr (2001) deployed an innovative computerized productivity measurement tool within a detailed comparative analysis of the on-site performance between the UK and French divisions of a major UK construction corporation. Also, these comparative studies could highlight successful methodologies, allowing GDOT to replicate high-performance strategies across multiple projects. All in all, through the integration of benchmarking historical data, GDOT could reduce uncertainty and improve project predictability, ensuring schedules remain realistic and achievable.

8.3 Granular Activity Tracking for Task-Level Optimization

Productivity for construction industry could be assessed at three levels: task, project and industry (T. Cheng et al., 2013). Traditional approaches for measuring productivity relies on project-level information systems, direct observation methods, and survey/interview-based methods (Gong & Caldas, 2010). Application of these methods have demonstrated limitations such as high cost of

manual data collection, risk regarding interference of activities under observation, and the tendency of inaccurate data production (T. Cheng et al., 2013). Moreover, these methods are manual intensive, leading to delayed information exchange and analysis (Cheok et al., 2000). Consequently, instead of tracking productivity at a macro level, granular tracking focuses on individual construction phases and activities, such as grading, asphalt paving, and curing. By breaking down the entire construction project into smaller, measurable units, it could enhance the visibility into performance at a micro-level, allowing managers to identify inefficiencies and implement corrective actions. Since each phase is monitored separately, bottlenecks and inefficiencies that might go unnoticed in aggregate productivity tracking are now identified and paid more attention to.

To ensure accurate data collection for task-level productivity capturing, work sampling techniques and automated tracking systems are of great necessity. Originally developed by industrial engineer Leonard Tippett in 1927 (Gouett et al., 2011), work sampling is considered as a work measurement tool to control inputs. Then in 1960s, this term was adapted to the construction industry and became one of the methods for measuring construction productivity in 1986 (Gouett et al., 2011). Currently, work sampling is taken as a means to benchmark direct work rates for making improvements. However, according to Teizer et al. (2020), using work sampling method is effectful but resource demanding. This leads to the development of automated tracking and monitoring by analyzing work sampling data (Teizer et al., 2020). Using work sampling techniques and IoT-enabled sensors could provide real-time insights into workforce engagement, material movement, and equipment utilization (Gouett et al., 2011). Utilizing automated tracking systems could detect idle time and workflow interruptions, allowing managers to intervene in real-time to improve efficiency (T. Cheng et al., 2013).

Besides work sampling and automated tracking systems, AI-powered performance dashboards should also be integrated for visualizing granular productivity trends, enabling real-time comparisons between planned and actual performance. Pourrahimian et al. (2024) proposed a warning dashboard system for proactive decision-making, using historical data and machine learning algorithms. This dashboard system could provide invaluable and semi-real-time alerts to the project manager to avoid productivity lapses. Moreover, Gledson et al. (2024) proposed a webbased design management prototype dashboard to enhance design management productivity in construction firms through monitoring design production, assessing trends of designer performance, and targeting at technical queries and Request for Information (RFI). These dashboards could allow managers to adjust schedules dynamically based on real-time progress reports, ensuring work continuity with the minimum downtime.

8.4 Best Practices of Capturing Productivity Rates for GDOT to Adopt in the Future

In order to enhance productivity capturing, scheduling, resource utilization, and sustainability, the following best practices are suggested in the future infrastructure projects. Five purposes (accuracy, consistency, actionability, transparency, and scalability) are marked align with the best practices. Detailed practical actions are also included in Table 3.

Table 3. Best Practices of Capturing Productivity Rates for Futuristic Improvement

Create structured data collection templates which consists of task duration, crew size, material usage, and equipment efficiency. Collection Framework (Consistency) Ensure consistent units of measurement (e.g., labor hours/cubic yard of earth work, paving rate in lane-miles per day). Standardize data entry processes across contractors, subcontractors, and GDOT field teams to eliminate discrepancies. Replace manual reporting with mobile applications and tablet-based input forms for on-site data collection. Integrate GDOT-wide digital productivity tracking platforms, such as Procore, Autodesk BIM 360, or Oracle Primavera, ensuring seamless real-time data entry and access. Create a centralized database where productivity data is stored and accessible for long-term analysis Automate Data Validation and Error Detection Process (Accuracy & Actionability) Utilized GPS and IoT-Enabled Equipment Tracking Systems (Accuracy & Utilize Mearable Technology for Workforce Productivity Tracking (Accuracy & Actionability) Utilize Wearable Technology for Workforce Productivity Tracking (Accuracy & Actionability) Utilize Drone Technology and LiDAR-Based Work Progress Monitoring (Accuracy) Utilize Drone Technology and LiDAR-Based Work Progress Monitoring (Accuracy) Utilize Drone Technology and LiDAR-Based Work Progress Monitoring (Accuracy) Utilize drone ameras to track task progress to ensure reported
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Standardize data entry processes across contractors, subcontractors, and GDOT field teams to eliminate discrepancies. Replace manual reporting with mobile applications and tablet-based input forms for on-site data collection. Accuracy & Integrate GDOT-wide digital productivity tracking platforms, such as Procore, Autodesk BIM 360, or Oracle Primavera, ensuring seamless real-time data entry and access. Create a centralized database where productivity data is stored and accessible for long-term analysis Apply Al-based error-checking algorithms which mark anomalies automatically (e.g., inconsistent labor hours, unrealistic productivity rates). Use cross-validation techniques by comparing contractor-reported productivity with sensor-based data and historical benchmarks. Attach GPS trackers and IoT sensors to heavy equipment (e.g., bulldozers, pavers, excavators) to monitor active usage vs. idle time. (Accuracy & Actionability) Utilize Mearable Technology for Workforce Productivity Tracking (Accuracy & Mandate workers to wear smart helmets, RFID tags, or biometric wearables to capture actual labor engagement vs. idle periods. Use AI-driven models to identify and classify between productive and non-productive activities based on movement and location data. Implement RFID/NFC-enabled job cards to automatically log worker arrival, task duration, and completion time. Deploy drones with LiDAR scanning to capture daily progress in grading, earthwork, and paving activities. Compare real-time aerial images with schedule work plans to validate productivity data automatically.
subcontractors, and GDOT field teams to eliminate discrepancies. Replace manual reporting with mobile applications and tablet-based input forms for on-site data collection. Integrate GDOT-wide digital productivity tracking platforms, such as Procore, Autodesk BIM 360, or Oracle Primavera, ensuring seamless real-time data entry and access. Create a centralized database where productivity data is stored and accessible for long-term analysis Automate Data Validation and Error Detection Process (Accuracy & Actionability) Utilized GPS and IoT-Enabled Equipment Tracking Systems (Accuracy & Actionability) Utilize Wearable Technology for Workforce Productivity Tracking (Accuracy & Actionability) Utilize Wearable Tracking (Accuracy & Mandate workers to wear smart helmets, RFID tags, or biometric wearables to capture actual labor engagement vs. idle periods. Utilize Drone Technology and LiDAR-Based Work Progress Monitoring Subcontractors, and GDOT field teams to eliminate discrepancies. Replace manual reporting with mobile applications and tablet-based collection. Integrate GDOT-wide digital productivity tracking glatforms, such as Procore, Autodesk BIM 360, or Oracle Primavera, ensuring seamless real-time data entry and access. Create a centralized database where productivity automatically (e.g., inconsistent labor hours, unrealistic productivity with sensor-based data and historical benchmarks. Attach GPS trackers and IoT sensors to heavy equipment (e.g., bulldozers, pavers, excavators) to monitor active usage vs. idle time. Utilize machine learning algorithms to detect patterns in equipment efficiency, identifying potential downtime causes. Utilize machine learning algorithms to detect patterns in equipment
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Based Work Progress Monitoring Compare real-time aerial images with schedule work plans to validate productivity data automatically.
Monitoring validate productivity data automatically.
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(Accuracy) Use drone cameras to track task progress to ensure reported
productivity align with actual execution.
Establish a Productivity Archive multi-year productivity data for key activities such as
Data Warehouse for earthwork, paving, and bridge construction.
Long-Term Analysis Maintain a benchmark repository for comparing new projects with
(Accuracy & historical performance trends.
Actionability) Use machine learning models to analyze past GDOT projects and
determine expected productivity rates under different conditions.
Develop a predictive scheduling tool which recommends resource
allocation strategies based on past performance.
Analyze weather-based productivity trends to account for seasonal
variations.

	T
	Integrate GIS-based site condition mapping to predict terrain-
	related productivity impacts.
Develop AI-Powered	Use cloud-based platforms to visualize real-time productivity data
Interactive Dashboards	in dashboard formats.
(Actionability &	Provide role-based access to different GDOT stakeholders (e.g.,
Transparency)	managers, contractors, and filed engineers) to view customized
	insights according to project requirements.
	Configure early warning systems which mark projects falling
	behind expected productivity rates.
	Set predefined thresholds for labor efficiency, equipment
	utilization, and task completion rates, triggering alerts if deviations
	occur.
	Allow dynamic work allocation through automated scheduling
	adjustments in response to real-time performance data.
Incorporate Productivity	Mandate that all GDOT contractors submit real-time productivity
Reporting as a	data through approved tracking platforms.
Contractual Requirement	Establish performance-based incentives for contractors who
(Transparency &	consistently achieve high productivity tracking compliance.
Scalability)	
Create a Contractor	Develop a grading system for contractors based on historical
Productivity Evaluation	productivity performance, reporting accuracy and efficiency
Program	improvements.
(Transparency &	Utilize these evaluations for future bid selection and contract
Scalability)	renewals.
	

In conclusion, by integrating real-time tracking, automation, benchmarking, and contractor compliance measures, GDOT could establish a sustainable, data-driven productivity measurement system to ensure the productivity data is accurate, consistent, actionable, transparent, and scalable.

9. DEVELOPMENT AND BETA-TESTING OF THE SCHEDULING ASSISTANT TOOLKIT

9.1 Conceptual Framework of the Scheduling Assistant Toolkit

Rationale for Advanced Scheduling Methods

The inception of the Scheduling Assistant Toolkit began with recognizing that existing project scheduling software often lacks a mechanism to incorporate nuanced factors such as overlapping costs, rework risks, and the interplay between evolution, reliability and sensitivity scores. Based on these complexities, the Toolkit seeks to move beyond static Gantt charts by offering dynamic, real-time insights. Leveraging Python's Dash framework for interactive web applications, together with Plotly for rich data visualizations, the development team targeted the specialized needs of GDOT. Specifically, the project aims to capture advanced scheduling considerations such as partial overlaps, rework costs, and critical path analysis with one integrated solution.

Code Modules and Structure

In the Toolkit's underlying code (see Scheduling_Toolkit_app.py in the Appendix), multiple Python functions and Dash callbacks create the application's logic. Here are some key functions within the code:

- parse_csv(contents): this function validates and transforms input csv files, converting data strings into Python datetime objects while mapping each row to a standardized structure for scheduling analysis.
- calculate_critical_path(activities): this function executes a forward or backward pass algorithm to determine earliest start (ES), earliest finish (EF), latest start (LS), and latest finish (LF) times, ultimately identifying tasks on the critical path (activities with 0 slack).
- overlap_two_activities(activities, actA, actB, overlap_days): this function shifts the successor activity by a user-defined number of days for partial overlap simulations.
- get_project_duration(activities): this function computes the total project duration in days from the ES to the LF across all tasks.

With the aid of Dash callbacks, these functions connect user interactions (e.g., csv file upload or tab selection) to dynamic updates of tables, graphs, and textual outputs.

9.2 Incorporation of Risk and Cost Analysis

Rework Risks and Overlapping Strategies

While standard Critical Path Methodologies (CPM) focus primarily on task dependencies durations, GDOT projects prefer multiple potential rework loops and partial overlaps which introduce substantial complexity to both schedule and cost . The Toolkit, therefore, integrates a risk-of-rework parameter to quantify the potential financial and schedule impacts when tasks overlap. These calculations are managed in part by the store-activities and store-cp-data data structures implemented as Dash dcc.Store components, enabling the application to retain state across different user interactions.

Dual-Cost System

In order to capture both accelerated and delayed impacts, the Toolkit employs two cost components:

- Direct Overlap Cost: this cost is directly proportional to the overlap, and it's calculated by multiplying Risk of Rework per day and overlap_days (refer to Figure 7).
- Indirect Costs: based on the project's total duration, this cost is multiplied by a daily cost rate (e.g., \$200 per day in testing)

This dual-cost framework provides a balanced view of how schedule compression could affect overall expenditure.

9.3 Data Handling and CSV-Based Ingestion

Structured CSV File Upload

Users could upload a CSV file containing fields including *Activity Name*, *Evolution Rate*, *Sensitivity Score*, *Reliability Score*, *Start Date*, *End Date*, *Duration*, *Predecessor*, *Successor*, *Cost of Rework per Day*, *Probability of Rework*, *Risk of Rework per Day*. The parse_csv function validates these inputs, converts dates to Python datetime objects, and constructs a critical path diagram from Predecessor/Successor relationships. During initial testing, a synthetic schedule (tasks A through L) was repeatedly uploaded to validate correct parsing (see Figure 15).

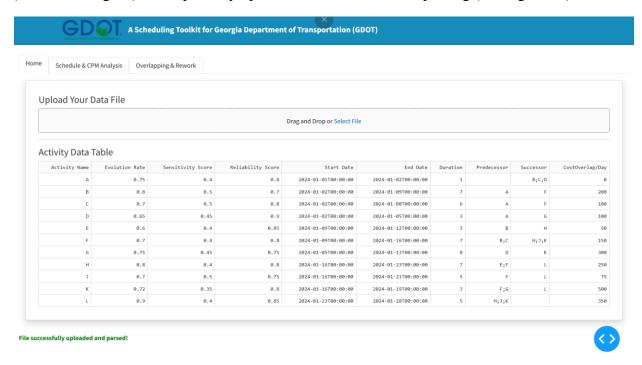


Figure 15. Display of User Interface for Structured CSV File Upload

9.4 Critical Path Detection and Visualization

Multi-Pass CPA Method

The calculate_critical_path function integrates a classic forward/backward pass to identify tasks with zero slack as critical. While standard in project management, the function includes additional logic to track the "longest chain" path in parallel branches, which is important for highway and infrastructure projects that feature multiple simultaneous starts or branching dependencies. Plotly Express is employed to produce a Gantt chart, color-coded by various metrics including Evolution Rate, Reliability Score, and Sensitivity Score (see Figure 16). In parallel, a time-scaled fence bar chart (similar to a custom timeline) highlights critical activities distinctly, helping project managers visualize slack or the lack thereof (see Figure 17). It is especially valuable to toggle

among coloring attributes to see how high-sensitivity or high-reliability tasks intersect with the critical path.

Schedule & CPM Analysis Baseline Gantt Color Gantt By: **Evolution Rate Evolution Rate** Sensitivity Score evolutionRate 0.9 Reliability Score В 0.85 D 0.8 0.75 0.7 0.65 0.6 Jan 7 2024 Jan 14 Jan 21 Jan 28

Figure 16. Gantt chart Section from the Scheduling Toolkit of the Synthetic Project

Date

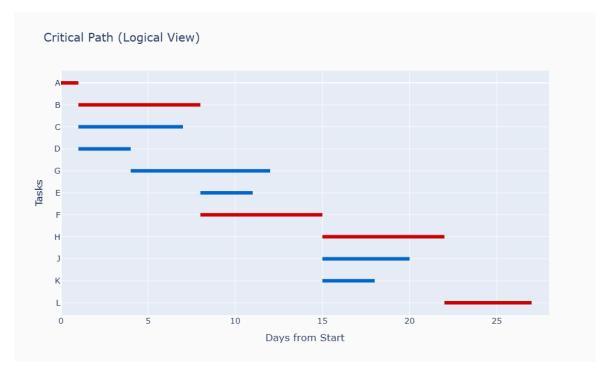


Figure 17. "Critical Path Diagram" Section from the Scheduling Toolkit of the Synthetic Project

9.5 Modeling Overlap and Rework Costs

Iterative Overlap Logic

One of the Toolkit's standout features is the ability to iteratively test overlapping scenarios. The overlap_two_activities function shifts a successor's start date by a user-specified overlap period, recalculating both the project duration and direct overlap costs. Automated routines then compare these scenarios to the baseline schedule to identify the net impact on total project cost. Recent beta-test iterations implemented the Toolkit's overlap logic within a 6-step methodology for project duration optimization. By focusing on critical activities with the *least expensive per-day overlap cost*, the system identifies pairs of tasks to overlap and assesses the resulting schedule and total cost. Here are the demonstrations for these tests using both Excel and the Toolkit interface.

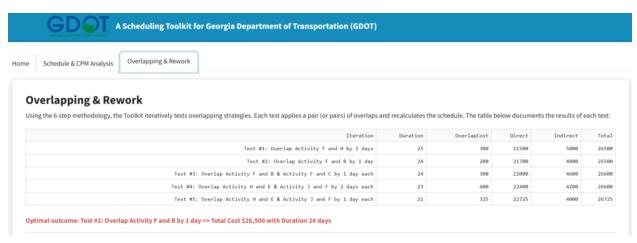


Figure 18. Overlapping and Rework Testing from the Scheduling Toolkit Interface

- Test #1: Overlapping Activity F and Activity H (\$150/day)
 - ❖ Yields a 25-day project duration
 - ❖ Direct Cost increases by \$300 due to overlap, saves \$400 in Indirect Cost due to 2 fewer days \$200/day
 - The new total cost is $\$21,200 + \$300 + (25 \times \$200) = \$26,500$ (see Figure 19)
 - Activity J emerges as a critical activity (see Figure 20).

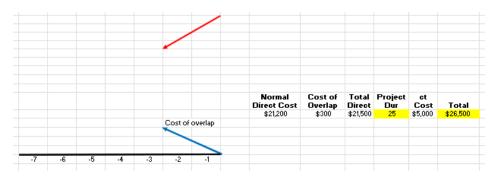


Figure 19. Total project cost with a 25-day Duration

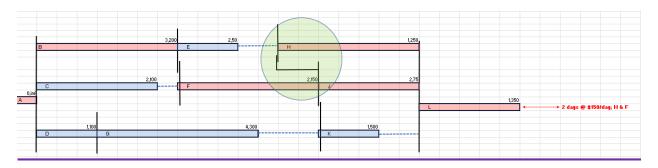


Figure 20. Time-scaled Fenced-Bar Chart with a 25-day Duration

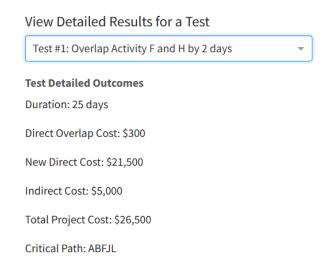


Figure 21. Detailed Results for Test #1 from the Scheduling Toolkit Interface

- Test #2: Overlapping Activity F and Activity B (\$200/day)
 - ❖ Yields a 24-day project duration
 - ❖ Direct Cost increases by \$200 due to overlap, saves \$200 in Indirect Cost due to 1 fewer day \$200/day
 - The new total cost is $$21,500 + $200 + (24 \times $200) = $26,500$ (see Figure 22)
 - ❖ Activity C emerges as a critical activity (see Figure 23).

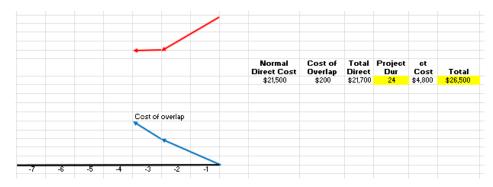


Figure 22. Total project cost with a 24-day Duration

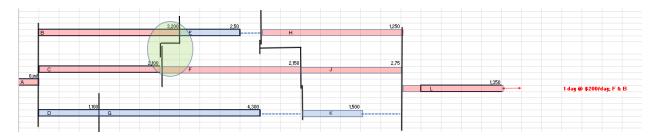


Figure 23. Time-scaled Fenced-Bar Chart with a 24-day Duration

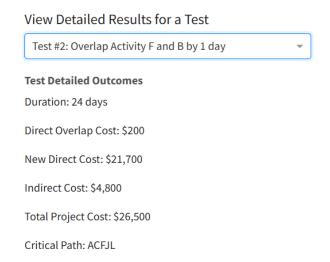


Figure 24. Detailed Results for Test #2 from the Scheduling Toolkit Interface

- Test #3: Overlapping Activity F and Activity B & overlapping Activity F and Activity C (\$200+\$100/day)
 - Yields a 23-day project duration
 - ❖ Direct Cost increases by \$300 due to overlap, saves \$200 in Indirect Cost due to 1 fewer day \$200/day
 - The new total cost is $\$21,700 + \$300 + (23 \times \$200) = \$26,600$ (see Figure 25)
 - ❖ Activity E emerges as a critical activity (see Figure 26).

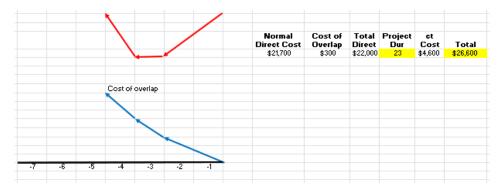


Figure 25. Total project cost with a 23-day Duration

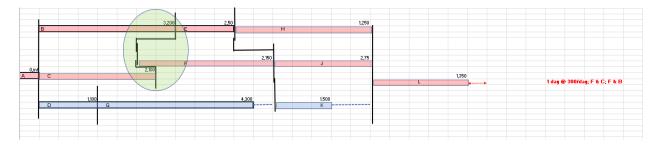


Figure 26. Time-scaled Fenced-Bar Chart with a 23-day Duration

View Detailed Results for a Test Test #3: Overlap Activity F and B & Activity F and C by 1 ...

Test Detailed Outcomes

Duration: 24 days

Direct Overlap Cost: \$300

New Direct Cost: \$22,000

Indirect Cost: \$4,600

Total Project Cost: \$26,600

Critical Path: ACEJL

Figure 27. Detailed Results for Test #3 from the Scheduling Toolkit Interface

- Test #4: Overlapping Activity H and Activity E & overlapping Activity J and Activity F (\$50+\$150/day)
 - ❖ Yields a 21-day project duration
 - ❖ Direct Cost increases by \$400 due to overlap, saves \$400 in Indirect Cost due to 2 fewer days \$200/day
 - The new total cost is $$22,000 + $400 + (21 \times $200) = $26,600$ (see Figure 28)
 - ❖ No new critical activities emerge (see Figure 29).

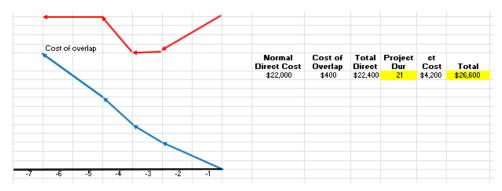


Figure 28. Total project cost with a 21-day Duration

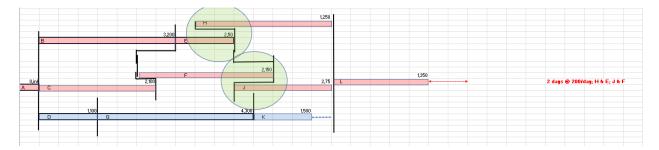


Figure 29. Time-scaled Fenced-Bar Chart with a 21-day Duration

View Detailed Results for a Test

Test #4: Overlap Activity H and E & Activity J and F by 2

Test Detailed Outcomes

Duration: 23 days

Direct Overlap Cost: \$400

New Direct Cost: \$22,400

Indirect Cost: \$4,200

Total Project Cost: \$26,600

Critical Path: ABFHL

Figure 30. Detailed Results for Test #4 from the Scheduling Toolkit Interface

- Test #5: Overlapping Activity H and Activity E & overlapping Activity J and Activity F
 (\$250+\$75/day)
 - Yields a 20-day project duration
 - ❖ Direct Cost increases by \$325 due to overlap, saves \$200 in Indirect Cost due to 1 fewer day \$200/day
 - Arr The new total cost is \$22,400 + \$325 + (20 × \$200) = \$26,725 (see Figure 31)
 - ❖ No new critical activities emerge (see Figure 32).

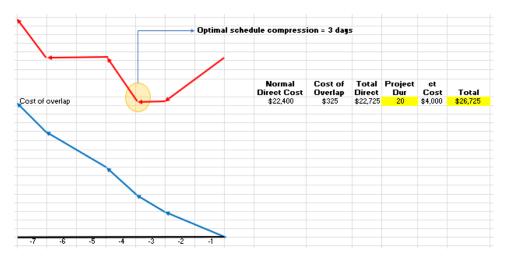


Figure 31. Total project cost with a 20-day Duration

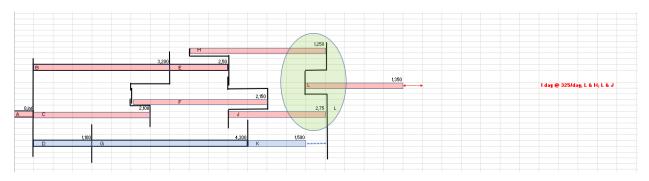


Figure 32. Time-scaled Fenced-Bar Chart with a 20-day Duration

View Detailed Results for a Test

Test #5: Overlap Activity H and E & Activity J and F by 1

Test Detailed Outcomes

Duration: 21 days

Direct Overlap Cost: \$325

New Direct Cost: \$22,725

Indirect Cost: \$4,000

Total Project Cost: \$26,725

Critical Path: ABFHL

Figure 33. Detailed Results for Test #4 from the Scheduling Toolkit Interface

Every scenario recalculates the project's Direct Cost by summing a base direct cost with the overlap cost, while Indirect Costs derive from the revised project duration (e.g., \$200/day in the example). The Toolkit automatically documents these calculations in a results table, enabling rapid "what-if" analysis to see when overlap is no longer cost-effective. In the synthetic example, 24

days yields an optimal compromise: the overlap costs incurred are balanced by the indirect cost savings. Any further compression (23, 21, or 20 days) increases direct rework expenses beyond the offset that shorter durations provide. In conclusion, the Toolkit confirms that a 24-day duration (Test #2) yields the best new cost outcome (\$26,500) for the synthetic schedule. Attempting to shorten the schedule below 24 days simply increases overlap costs faster than the indirect savings.

9.6 Future Improvement of the Scheduling Assistant Toolkit

One of the key areas for future enhancement in the Scheduling Assistant Toolkit is the integration of Evolution Rate, Sensitivity Score, and Reliability Score into the Risk-Cost Analysis. Currently, the toolkit utilizes critical path methods and predefined rules for determining the optimal level of activity overlaps. However, incorporating these three parameters would provide a more data-driven and dynamic approach to scheduling optimization, allowing for a more nuanced understanding of the trade-offs between schedule optimization and rework risks.

10. CONCLUSION AND NEXT STEPS

The Scheduling Assistant Toolkit has been developed to address inefficiencies in GDOT's current scheduling processes, providing a structured framework for optimizing construction schedules. Through a systematic review of existing scheduling methodologies, the toolkit integrates best practices in schedule overlapping and risk-cost analysis to enhance project efficiency. A key component of this research is the benchmarking analysis of location and trade productivity, which highlighted critical inefficiencies such as crew handoffs, work discontinuities, inefficiencies, and ineffectiveness. By identifying these bottlenecks, this research establishes a foundation for data-driven scheduling improvements that could significantly reduce project delays and enhance overall productivity.

To ensure the practical adoption of this methodology, the next steps would be focusing on implementing and refining the toolkit for real-world applications. The development of a computerized schedule overlapping tool will allow project managers to evaluate different time-risk-cost trade-offs, leading to more informed decision-making. Pilot testing on GDOT projects is also essential to validate the toolkit's effectiveness and refine its recommendations based on actual field conditions. Additionally, a user training and adoption strategy will be implemented to equip GDOT personnel with the necessary skills to utilize the toolkit effectively, ensuring smooth integration into project workflows.

For long-term success, the toolkit must be seamlessly integrated with GDOT's existing scheduling systems, such as Primavera P6 and Microsoft Project, to maximize its usability. Furthermore, the framework must support scalability and continuous improvement, allowing it to adapt to more complex infrastructure projects and evolving industry practices. Future enhancements should explore the incorporation of real-time productivity tracking and AI-driven decision-making to further optimize scheduling efficiency. By pursuing these strategic next steps, GDOT can establish a robust, data-driven approach to construction scheduling, ultimately leading to improved project delivery and reduced costs.

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